# Analysis of capacitive proximity sensing as basis for human vehicle interfaces

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# Erklärung zur Dissertation

Hiermit versichere ich die vorliegende Dissertation selbständig nur mit den angegebenen Quellen und Hilfsmitteln angefertigt zu haben. Alle Stellen, die aus Quellen entnommen wurden, sind als solche kenntlich gemacht. Diese Arbeit hat in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegen.

Darmstadt, den 21/03/2021 Sebastian Frank

# Abstract

People spend a lot of time in vehicles. Driving involves risks that are mitigated by passive and active safety systems. Active safety systems prevent accidents from happening in the first place. Human machine interfaces (HMI) are needed to monitor the driver's behavior and capture driver's input. This presents challenges based on environmental, vehicle interior, and user characteristics. Vehicles are directly exposed to the environment. Sensors have to cope with both rapid light changes and complete darkness. Vehicle interiors contain geometries that obscure parts of the human body. Sensors that require a line of sight may therefore be at a disadvantage. Sensor positioning is also limited by vehicle geometry. Sensors that require additional mounting impact the design and result in an obtrusive system. Systems that can be integrated invisibly into existing vehicle structures are less obtrusive and have less impact on the design. Parts of the user must also be monitored in free air, which makes contact-based scanning systems unsuitable. Some sensor systems are capable of monitoring the entire body, but still have to deal with the requirements of vehicle users. People will wear different clothing or glasses. User monitoring must be enabled regardless of this condition. People are also becoming sensitive to their personal data. This can be crucial for the acceptance of systems. Systems must also comply with regulations such as "Privacy by Design" which is required in the European Union. Privacy must therefore be preserved.

I argue that capacitive proximity sensors are capable of dealing with the above challenges. Due to the physical principle, illumination changes are not an issue, and they can sense through insulators. Capacitive proximity sensors (CAPS) can therefore be used in existing vehicle structures, both in close proximity and without contact with the object to be monitored. In addition, they are often said to maintain privacy. Based on the challenges and capabilities of CAPS, three research questions emerge:

- RQ1: How can we use existing vehicle structures to enhance or substitute vehicular HMI using CAPS?
- RQ2: How can we use existing vehicle structures to provide new ways of human computer interaction using CAPS?
- RQ3: Can CAPS contribute to the acceptance of vehicular HMI with regard to privacy concerns?

To find evidence to support these research questions, I focused on systems that help users drive safely. Cameras are commonly used in HMI. Because they require line of sight, affect interior design, and capture data that creates privacy concerns, they may not be the best choice. CAPS are therefore an opportunity to change the modality. Several applications are developed that provide evidence that the use of CAPS is beneficial for vehicle HMI. Each application is developed following a common process with the goal of meaningful uses. Each application is based on accident statistics and related research, so that real-world problems are addressed. This entails analysis of driving issues, prototype implementations of sensor topologies, and algorithms for attention monitoring, child monitoring, authentication, and gesture recognition in vehicles. One will additionally receive best practices for CAPS data labeling, which is crucial for supervised learning methods that are considered helpful. Privacy compliant behavior is analyzed in this thesis. Vehicle HMI are therefore analyzed with regard to privacy concerns and regulations. The user's data protection perspective is also captured in a survey. This is necessary to find indications that CAPS is not only an alternative from a technical point of view. It is also an alternative that could be in the user's favor.

# Zusammenfassung

Motorisierte Fahrzeuge sind für viele Menschen das wichtigste Transportmittel. Um zum Beispiel den Arbeitsweg zu bestreiten, ist es, bezogen auf die Zeiteffizienz, oft alternativlos. Mit der regen Nutzung von Fahrzeugen geht ein erhöhtes Verkehrsaufkommen einher, sodass die Gefahr von Verkehrsunfällen, bei denen Verkehrsteilnehmer schwer verletzt werden können, steigt. Die Folgen von Unfällen werden durch passive Sicherheitssysteme wie Gurtsysteme oder Airbags vermindert. In dieser Arbeit geht es um Mensch-Maschine-Schnittstellen im Fahrzeug, die bei aktiven Sicherheitssystemen verwendet werden. Diese Systeme versuchen Unfälle zu verhindern. Diese Mensch-Maschine-Schnittstellen werden zum Beispiel eingesetzt, um den Zustand von Fahrer und Mitfahrern zu überwachen. So kann zum Beispiel vor Unachtsamkeit gewarnt werden. Unachtsamkeit entsteht auch, wenn Fahrer Bedienelemente in einer Weise betätigen müssen, bei der sich ihre Aufmerksamkeit von der Straße auf Bedienelement richtet. Mensch-Maschine-Schnittstellen, in Form von Gestensteuerung, werden eingesetzt, sodass der Fahrer seinen Blick auf die Straße richten kann. Diese Schnittstellen basieren auf Sensoren, welche die zu überwachende Eigenschaft digitalisieren können. Zu diesen Schnittstellen zählen zum Beispiel Systeme, die Müdigkeit und nachlassende Aufmerksamkeit des Fahrers erkennen können. Weiterhin entsteht durch das voranschreiten der Entwicklung von hochautomatisiertem Fahren der Bedarf, dass der Fahrer jederzeit in der Lage sein muss, die Kontrolle über das Fahrzeug wieder zu übernehmen. Deshalb ist es auch hier wichtig die Lage des Fahrers zu überwachen, um seine Verfügbarkeit einschätzen zu können. Neben der Müdigkeit des Fahrers können auch weitere Gegebenheiten zu gefährlichen Situationen führen. Jede Ablenkung des Fahrers, die vermieden werden kann, mindert das Risiko. Da erkannt wurde, dass herkömmliche Anzeige- und Bedienelemente zu erhöhter Ablenkung führen, werden im Fahrzeug Systeme wie Head-Up Displays eingesetzt. Zudem wurde die Möglichkeit erkannt, dass Gestensteuerung anstelle von Bedienelementen wie berührungsempfindlichen Anzeigen oder Taster dazu führen kann, dass der Fahrer seinen Blick länger auf die Fahrsituation richtet. Außerdem sollten nur authentifizierte Personen das Fahrzeug führen. Im einfachsten Fall dient der Fahrzeugschlüssel der Authentifizierung. Schlüssel können verloren gehen oder entwendet werden. Biometrische Eigenschaften von Menschen werden zur eindeutigen Identifikation benutzt. Ein Problem entsteht hier dadurch, dass biometrische Daten nicht geändert werden können. Sobald die Daten unwissentlich an Dritte weitergegeben werden, sind Personen im Besitz empfindlicher Daten, die zur Authentifizierung dienen. Aber auch Systeme wie gezeichnete Muster auf Bildschirmen haben Nachteile. Die Spuren der Finger auf den Bildschirmen können sichtbar gemacht werden und so können Passwörter erkannt werden. Sensoren die diese Herausforderungen begegnen, müssen auch mit einer Reihe weiterer Gegebenheiten speziell in Fahrzeugen zurechtkommen. Zum Beispiel müssen Umweltbedingungen bei der Sensorauswahl bedacht werden. Weiterhin bietet der Fahrzeuginnenraum weitere Beschränkungen bei der Montage von Sensoren. Letztlich ist es auch der Fahrzeugnutzer, der Anforderungen an Mensch-Maschine-Schnittstellen stellt, die beachtet werden müssen. Fahrten bei Tag wie auch bei Nacht führen zu wechselnden Lichtbedingungen. Weiterhin sind Sensoren in Fahrzeugen starken Temperaturschwankungen ausgesetzt. Sensoren müssen mit diesen unterschiedlichen Bedingungen umgehen können. Elemente im Innenraum können Teile des menschlichen Körpers abdecken. Sensoren, die eine direkte Sichtlinie benötigen, können hierdurch im Nachteil sein. Auch die Positionierung von Sensoren kann durch die Geometrie des Fahrzeuginnenraums eingeschränkt sein. Wenn für die Positionierung sichtbare Montagepositionen geschaffen werden müssen, kann sich dies negativ auf die Innenraumgestaltung auswirken. Außerdem werden die Sensoren so für den Nutzer sichtbar was diesen stören könnte. Ein System, das in ex-

istierende Fahrzeugstrukturen integriert werden kann, ist deshalb weniger aufdringlich und hat einen geringeren Einfluss auf die Fahrzeuginnenraumgestaltung. Ein Sensorsystem muss, trotz unaufdringlicher Positionierung, in der Lage sein, alle erforderlichen Teile des menschlichen Körpers zu überwachen, sodass die Funktion der Mensch-Maschine-Schnittstelle gewährleistet ist. Bestimmte Teile des menschlichen Körpers müssen auch dann überwacht werden, wenn diese keinen mechanischen Kontakt zum Sensor herstellen. Sensoren die einen mechanischen Kontakt benötigen, wie zum Beispiel Drucksensoren, sind dann nicht geeignet. Auch wenn einige Sensorsysteme die Fähigkeit haben, benötigte Teile des menschlichen Körpers zu überwachen, müssen dennoch die spezifischen Anforderungen von Fahrzeugnutzern erfüllt werden. Ähnlich wie sich ändernde Lichtverhältnisse sind bildgebende Verfahren auch hier betroffen. Es ist natürlich, dass Menschen in Fahrzeugen verschiedene Kleidung oder Brillen tragen, sodass Sensoren auch hier Daten aufzeichnen müssen, die eine Überwachung des Nutzers garantieren, unabhängig von diesen Gegebenheiten. Nutzer stellen weitere Bedingungen an Sensorsysteme in Fahrzeugen. Besonderes Augenmerk richte ich auf das Privatsphäreempfinden von Menschen. Menschen werden immer sensibler, wenn es um ihre persönlichen Daten geht. Deshalb spielen Privatsphärebedenken eine große Rolle in unserem täglichen Leben und können sehr wichtig für die Akzeptanz von Systemen sein. Personen die Bedenken hinsichtlich ihrer Privatsphäre haben können in einer Form reagieren, die die Mensch-Maschine-Schnittstelle deaktiviert. Deshalb wird von manchen Nutzern die bereits ab Werk verbaute Kamera in Monitoren verdeckt. Mensch-Maschine-Schnittstellen im Fahrzeug sollten daher die Privatsphäre des Nutzers respektieren. Neben der subjektiven Wahrnehmung von Nutzern, wurden in Regionen wie der Europäischen Union Verordnungen verabschiedet, die das Sammeln von persönlichen Daten reglementieren. Diese Verordnung, die Datenschutzgrundverordnung, schreibt Datenschutz bei der Gestaltung und per Grundeinstellung vor und betrifft Mensch-Maschine-Schnittstellen im Fahrzeug.

Auf der Grundlage von Recherche und eigener Forschung sage ich, dass diese Herausforderungen mit kapazitiven Näherungssensoren angegangen werden können. Diese Sensoren sind unabhängig von Lichtbedingungen der Umgebung. Außerdem haben sie die Fähigkeit, durch nicht-leitende Materialien hindurch zu messen. Wechselnde Kleidung stellt daher keine Beschränkung dar. Außerdem benötigen kapazitive Näherungssensoren keinen mechanischen Kontakt. Aufgrund dieser Eigenschaften können kapazitive Näherungssensoren im Inneren von Fahrzeugstrukturen verbaut werden, unter der Voraussetzung, dass zwischen der Messelektrode der Sensoren und des zu überwachenden Objektes kein objektunabhängiges leitendes Medium angebracht ist. Dadurch ist mechanischer Kontakt zu den Sensoren ebenso möglich wie auch die Überwachung von Objekten in der Luft. Weiterhin wird kapazitiven Näherungssensoren oft das Attribute privatsphäreschützend gegeben. Dies wird dadurch begründet, dass keine Aufnahmen vom Gesicht des Nutzers aufgezeichnet werden. Aufgrund dieser Eigenschaften und den genannten Herausforderungen für Mensch-Maschine-Schnittstellen im Fahrzeug konnte ich drei Forschungsfragen ausarbeiten, die den Kern dieser Arbeit darstellen:

- RQ1: Wie können kapazitive Näherungssensoren in bestehenden Fahrzeugstrukturen genutzt werden, sodass Mensch-Maschine-Schnittstellen im Fahrzeug ersetzt oder unterstützt werden können?
- RQ2: Wie können kapazitive Näherungssensoren in bestehenden Fahrzeugstrukturen genutzt werden, um neue Möglichkeiten der Interaktion im Fahrzeug zu schaffen?
- RQ3: Können kapaztive Näherungssensoren zur Akzeptanz, im Hinblick auf Datenschutzbedenken, von Mensch-Maschine-Schnittstellen im Fahrzeug beitragen?

Um Hinweise für Forschungsfrage RQ1 zu finden, werden existierende Mensch-Maschine-Schnittstellen im Fahrzeug, aus der Forschung wie auch aktuell gefertigten Fahrzeugen, analysiert. Es gibt eine Vielzahl von Anwendungen für solche Systeme im Fahrzeug. Deshalb musste für diese Arbeit eine Auswahl getroffen werden. Entschieden habe ich mich für Mensch-Maschine-Schnittstellen, die die Sicherheit für Fahrer und Beifahrer erhöhen. Im Speziellen geht es um die Überwachung der Aufmerksamkeit des Fahrers und des Zustandes eines Kindes, dass in einem Kindersitz transportiert wird. Zur Überwachung werden hier oft Kameras eingesetzt,

die zum Beispiel Bilder vom Gesicht des Fahrers aufzeichnen. In diesem Fall sind die genannten Probleme von Mensch-Maschine-Schnittstellen präsent. Die Aufnahme von Bildern des Gesichtes können zu Problemen hinsichtlich der Privatsphäre führen. Außerdem müssen Kameras bei der Gestaltung des Innenraums berücksichtigt werden, da diese eine Sichtlinie zum Untersuchungsobjekt benötigen. Hinweise zur Forschungsfrage RQ1 können dabei helfen, diese Probleme anzugehen. In dieser Arbeit wurden zu dieser Forschungsfrage zwei existierende Fahrzeugstrukturen mit kapazitiven Näherungssensoren untersucht. Auf Grundlage der Messausgabe dieser Sensoren und einer anschließenden statistischen Verarbeitung, können Emissionen des Menschen und dadurch Symptome erkannt werden. Eines dieser Systeme ist die Überwachung der Aufmerksamkeit und Müdigkeit des Fahrers. Durch die Nutzung der Fahrzeugstruktur Fahrersitz, indem kapazitive Näherungssensoren eingebunden werden, konnten relevante Symptome zur Aufmerksamkeit erkannt werden. Neben dem Fahrersitz wurde ein Kindersitz als weitere Fahrzeugstruktur mit kapazitiven Näherungssensoren ausgestattet. Aufgrund dieses Aufbaus können physiologische Merkmale des Kindes erkannt werden. Beide Anwendungen, die Fahrerüberwachung und die Überwachung des Kindes, wurden in Nutzerstudien evaluiert. Die Nutzerstudien fanden unter Labor- oder realen Bedingungen statt. Auf Grundlage der Evaluation dieser Studien kann darauf geschlossen werden, dass kapazitive Näherungssensoren in Kombination mit existierenden Fahrzeugstrukturen und angemessenen Verarbeitungsalgorithmen ein System formen können, das in der Lage ist wichtige Symptome und menschliche Emissionen von Fahrern und Beifahrern (Kindern) zu erkennen, sodass existierende Mensch-Maschine-Schnittstellen im Fahrzeug unterstützt werden können.

Für Forschungsfrage RQ2 wird die Perspektive, von interaktionslosen Mensch-Maschine-Schnittstellen hin zu Systemen, die zur Operation auf menschliche Eingaben, beziehungsweise Interaktion angewiesen sind, gewechselt. Ähnlich wie in Forschungsfrage RQ1 habe ich für die Untersuchung von Forschungsfrage RQ2 Anwendungen ausgewählt, die durch die Interaktionsmöglichkeit die Sicherheit im Fahrzeug verbessern können. Auch im Bereich der Interaktion stützen sich viele Fahrzeughersteller und Forscher auf die Verwendung von Kameras, um zum Beispiel Hand oder Fußgesten zu erkennen. Auch hier entstehen ähnliche Probleme wie bei Mensch-Maschine-Schnittstellen ohne Interaktion. Aufgrund der Fähigkeit von kapazitiven Näherungssensoren, Veränderungen des elektrischen Feldes in ihrer Umgebung zu erkennen, sind diese auch für Interaktionssysteme geeignet. Interaktionssysteme können auf Basis kapazitiver Näherungssensoren unsichtbar in existierenden Fahrzeugstrukturen untergebracht werden. Aber ich zeige in dieser Arbeit nicht nur, dass Hand und Fußgesten von kapazitiven Näherungssensoren erkannt werden können. Ich zeige auch wie die Erkennung von Gesten für neue Anwendungen im Fahrzeug benutzt werden können, sodass die Sicherheit und der Komfort im Auto erhöht werden können. Für Forschungsfrage RQ2 wurden drei Anwendungen entwickelt, die die Fähigkeiten von kapazitiven Näherungssensoren in signifikanten Szenarien unter Beweis stellen. Eine Anwendung bezieht sich auf Head-Up Displays im Fahrzeug. Um dem Fahrer mehr Interaktionsmöglichkeiten mit dieser Anzeige zu ermöglichen, wurde ein System zur Erkennung von Zeigegesten entwickelt. Nutzer des Systems können auf Elemente in Ihrer Umgebung zeigen, unter der Voraussetzung das die Umgebung bereits segmentiert wurde. Anschließend kann die Anzeige im Head-Up Display entsprechend dieser Informationsanfrage angepasst werden. Dieses Szenario wurde gewählt, um die Möglichkeit zur Erstellung von Systemen auf Basis natürlicher Interaktion zu zeigen. Die Berücksichtigung von Bedingungen für natürliche Interaktion wurden in allen Anwendungen vorgenommen. In einem weiteren System wird ein neuer Weg zur Authentifizierung von Fahrern ermöglicht. Es handelt sich wiederum um ein System auf Basis der Erkennung von Handpositionen. Aufgrund der Gewissheit über die Position der Hand ist es für den Nutzer möglich, handschriftartige Bewegungen in die Luft zu zeichnen, die als Password für die Authentifizierung dienen. Weiterhin kann der Nutzer, aufgrund der robusten Erkennung der Handposition, Symbole und Buchstaben sowie kleine Wörter zeichnen. Hierdurch kann der Nutzer ein eigenes Passwort erstellen. Da er selbst die Gesten für das Passwort definiert, müssen keine symbolischen Gesten, die vom System vorgegeben werden, auswendig gelernt werden. In beiden Anwendungen, der Head-Up Display Unterstützung und im Authentifizierungssystem, wird das Lenkrad des Fahrzeugs als Basis für die

Sensoren benutzt. In einer dritten Anwendung zur Interaktion wird ein selten betrachteter Gegenstand zur Interaktionsmöglichkeit untersucht: Die Füße. In der Literatur wurden nur wenige Anwendungen gefunden, welche die Füße des Fahrers als Eingabe nutzen. Trotzdem wurde die Tätigkeit der Füße bereits früh in der Entwicklung von Assistenzsystemen, zum Beispiel durch Geschwindigkeitsregelanlagen, automatisiert. Durch die Nutzung der Füße als Eingabegerät können Hände entlastet werden. Weiterhin können aus der Haltung von Füßen Emotionen des Nutzers abgeleitet werden. Hierdurch kann die Erkennung von Fußpositionen neue Möglichkeiten zur Interaktion und Informationen über den Fahrerzustand liefern. Kapazitive Näherungssensoren wurden deshalb in den Fußraum des Fahrzeuges integriert und ein passender Algorithmus zur Datenverarbeitung wurde entworfen. Jede der Anwendungen für Forschungsfrage RQ2 wurde in einen Prototyp implementiert und in Nutzerstudien evaluiert. Auf Grundlage der Ergebnisse dieser Untersuchung zeigen kapazitive Näherungssensoren vielversprechende Möglichkeiten, wenn sie bei dem Design zur Unterstützung oder zur Ersetzung von existierenden Sensorsystemen im Fahrzeug eingesetzt werden. Zusätzlich werden auch hier, im Kontrast zu kamerabasierten Systemen, keine Bilder des Nutzers aufgezeichnet, sodass diese Sensoren dazu beitragen, dass ein möglicher Faktor für Privatsphärebedenken eliminiert wird.

Privatsphärebedenken leiten uns zur dritten Forschungsfrage RQ3. Kapazitive Näherungssensoren werden oft mit dem Attribut privatsphäreschützend belegt, im Besonderen, wenn diese mit kamerabasierten Systemen verglichen werden. Auch nach umfangreicher Literaturrecherche wurde keine Analyse oder Studie gefunden, die diese Eigenschaft von kapazitiven Näherungssensoren bestätigt. Gesucht wurde nach Analysen, die sich auf die Untersuchung von Systemen aus der Perspektive der Gesetzlage beziehen, wie auch nach Studien, die die subjektiven Wahrnehmungen von Fahrzeugnutzern in Bezug auf ihre Privatsphärebedenken untersuchen. Einrichtungen, wie die Europäische Union (EU), haben Verordnungen erlassen, welche die Entwicklung von Systemen auf der Grundlage von Privatsphärebedenken einschränken. Die Europäische Union im speziellen hat die Datenschutz-Grundverordnung erlassen, die sich auch auf Fahrzeuge bezieht. Auf Grundlage dieser Verordnung habe ich mehrere Mensch-Maschine-Schnittstellen im Fahrzeug analysiert. Besonders Artikel 25: *Datenschutz durch Technikgestaltung und durch datenschutzfreundliche Voreinstellungen*, wurde für die Analyse herangezogen. Die untersuchten Systeme basieren auf kapazitiven Näherungssensoren, wie auch auf anderen Sensoren und werden bereits in Serienfahrzeugen eingesetzt, wurden patentiert oder wurden in Publikationen veröffentlicht. Besonderes Augenmerk wird auf die Fähigkeit von Sensoren gelegt, die bei vergleichbaren Systemen mehr Informationen sammeln, als es für die Erfüllung ihrer Aufgabe nötig wäre. Aufgrund der Analyse wurde es fraglich ob Sensoren konform mit Artikel 25 sind, wenn diese die Fähigkeit haben, mehr Informationen zu sammeln als nötig. Die in dieser Analyse untersuchten Systeme zeigen, dass kapazitive Näherungssensoren weniger Informationen aufzeichnen und auf ihre Aufgabe fokussiert sind. Deshalb erscheinen diese in erhöhtem Maße konform, im Vergleich zu beispielsweise kamerabasierten Systemen. Gesetze spiegeln jedoch nicht unbedingt die Meinung von Fahrzeugnutzern wider. Deshalb habe ich auch eine Umfrage durchgeführt, die die subjektive Wahrnehmung von Fahrzeugnutzern wiedergibt. Mehr als 300 Teilnehmer haben an der Umfrage teilgenommen. In der Umfrage wurden die Teilnehmer zu ihren Präferenzen bezüglich Fahrerassistenzsystemen und den Einsatz von Kameras oder kapazitiven Näherungssensoren befragt. Die Teilnehmer der Umfrage stimmen überein, dass kapazitive Näherungssensoren weniger Privatsphärebedenken auslösen als Kameras, wenn diese im Auto verwendet werden.

In der vorliegenden Arbeit wird ein Prozess zur Entwicklung all dieser Lösungen erarbeitet, der die Entstehung der Anwendungen von der Idee bis zur Evaluation eines Prototyps begleitet. Hierdurch werden Sie in der Lage sein, den Einsatz von Sensoren in Mensch-Maschine-Schnittstellen im Fahrzeug besser zu bewerten. Insbesondere Richtlinien zum Einsatz von kapazitiven Näherungssensoren in Fahrzeugen und die besonderen Herausforderungen, die sich zum Beispiel bei der Klassifizierung von Daten von kapazitiven Näherungssensoren ergeben, werden Sie dabei unterstützen, signifikante Applikationen mit diesen Sensoren für das Fahrzeug zu erstellen und zu bewerten.

# Contents

# 1. Introduction


Figure 1.1.: Specification of this thesis' research area [Mic19, Sie20, Rea16, Vir18, Dai13, AUD18, Val19, Dor20, Bay, GPBB*13, BWKF15, Con]

This thesis combines three areas: capacitive proximity sensing, human machine interfaces and their use in vehicles. Their special characteristics, as well as advantages and disadvantages, will be explained later in this thesis. To introduce the field of research, we are guided by Figure 1.1. Various examples of human machine interfaces are shown on the left side of Figure 1.1. A human machine interface is anything which provides the ability to capture human emissions. For example, finger movements, eye movements and presence could be captured. A human machine interface is also anything where the human can capture emissions of the machine. For example, displays, sound output, vibration, or smell can be used in interfaces. A simple light switch can be a human machine interface as well as augmented reality glasses. The first narrowing of the research area is shown in the middle of Figure 1.1: human machine interfaces in cars. Everyday interfaces such as the touchscreen of a mobile phone are already integrated in the vehicle. Cars do not only provide touchscreens. For example, driver conditions can be monitored or pedestrians can be detected. Human machine interfaces in vehicles, as well as human machine interfaces in general, rely on sensor systems. Sensors must be accommodated in the vehicle in the smallest possible space. Common sensor systems in cars are cameras, microphones, and pressure sensors. A special sensor system is installed in some vehicle steering wheels: capacitive proximity sensors. This allows the driver's hands to be monitored as shown for example by Heller et al. [HS16]. This leads us to the right of Figure 1.1: sensors in vehicular human machine interfaces. This thesis deals with capacitive proximity sensors. Capacitive proximity sensors are not limited to vehicular applications. If one has studied publications on capacitive proximity sensors, one may have noticed their great impact on ambient assisted living. Researchers place capacitive proximity sensors under the floor of a living room, for instance. Applications based on these sensors can help elderly people to lead an independent life. Thanks to functions such as fall detection and

routine monitoring, they can live autonomously and safely [BHW12]. Capacitive proximity sensing applications also emerged in the office environment. Office chairs equipped with capacitive proximity sensors support office workers with exercises in short breaks [BSF15]. This thesis is not about office furniture or home applications with capacitive proximity sensing. This thesis is about the analysis of capacitive proximity sensing as the system of choice for human machine interfaces in vehicles.

The application of capacitive proximity sensors is widely used in the automotive industry. Suppliers like Hella [BSW06] or Continental [Hou13] provide key-less entry systems that detect the presence of a hand on the door handle with capacitive proximity sensors. These sensors are used, for example, as simple switches or buttons on the vehicle's infotainment display. The focus of the application is on very close interaction up to the touch. Capacitive proximity sensors are also used in applications where the user is more distant from the sensor. For example, bumper-mounted capacitive proximity sensors detect the presence of a foot. This triggers the opening of the trunk. An example manufacturer for such a system is Texas Instruments [Tex19]. This is very analogous to a simple switch, only with a more distant input. When it comes to more complex user input, such as gesture recognition or driver state detection, cameras seem to be the system of choice for vehicle manufacturers and suppliers [Bay18, DS 19, Gro16]. This thesis is not about simple switches. Based on this thesis, I promise that one will reconsider human machine interfaces in the vehicle. One will be able to form an opinion about capacitive proximity sensing and vehicular human machine interfaces. Even though this thesis shows that capacitive proximity sensors are well suited for complex automotive applications, this does not yet say anything about user acceptance of this system. For example, when it comes to reservations regarding privacy. Intentions of the legislation regarding privacy are also not reflected. This thesis therefore also compares the type of application of capacitive proximity sensors with existing systems in cars in terms of privacy. This will enable better evaluation of applications based on capacitive proximity sensors and other sensors from a technical and socio-economic point of view. In addition to investigating symptoms and privacy, this thesis investigates novel use of different vehicle structures with capacitive proximity sensors. These structures include the steering wheel, the vehicle's leg room, the driver seat and child seats.

## 1.1. Motivation

More and more driver assistance systems are being developed and used in vehicles. The number of sensors in vehicles is increasing accordingly. Radar sensors monitor the traffic in front of and behind the vehicle. Based on the information about the traffic, vehicle systems can detect situations that require emergency braking. 360° cameras integrated in the exterior mirrors enable automated parking. A Lidar installed to support autonomous driving vehicles can be used to avoid accidents with pedestrians [LTT*18]. In addition to these external sensors, driver information and monitoring devices are used inside the vehicle. Both human machine interfaces in vehicles and capacitive proximity sensing offer great opportunities for research. Opportunities for automotive applications range from comfort functions and gesture control to identification and authentication systems. For all these systems, there are preferred sensors in research. To highlight the usability of capacitive proximity sensing, problems from different areas of human machine interfaces and interaction in vehicles are investigated and addressed. All these systems have something in common: Human machine interfaces in vehicles should be easy to use. They should also preserve the user's privacy and be unobtrusive. Due to the size of the research area of human machine interfaces in vehicles, sub-areas that I consider to be very important for vehicle safety and comfort were selected. The selected sub-areas are driver and passenger monitoring, driver authentication, and gesture control.

These domains were selected to answer three research questions that form the foundation of this thesis. The first question is related to human machine interfaces without intended interaction. It is about human machine

interfaces that are installed to monitor drivers and passengers. The objective is to answer the question of how capacitive proximity sensors can be utilized in existing vehicle structures to enhance the human machine interfaces of vehicles by either substituting their sensors or adding other sensors. In this case, the acquisition of physiological or anthropometric conditions will contribute to answering this question. In the second research question, we shift our perspective from passive monitoring of passenger conditions to active interaction between the user and the vehicle. The purpose is to answer how existing vehicle structures can be used to enable new capabilities or improve human computer interaction in vehicles. Human machine interfaces in both research questions may face reservations from users. A third research question is hence formulated: How can capacitive proximity sensing contribute to the acceptance of human machine interfaces in vehicles. In this case, the focus is on the privacy-compliant behavior of the systems. In particular, two perspectives are addressed by this question. Perspective one concerns legal requirements for systems to behave in a privacy-compliant manner. Perspective two pertains to people's subjective privacy concerns regarding human machine interfaces in vehicles. These three research questions are presented in the following list. Abbreviations are used in the following work.

- RQ1: How can we use existing vehicle structures to enhance or substitute vehicular human machine interfaces using capacitive proximity sensing?
- RQ2: How can we use existing vehicle structures to provide new ways of human computer interaction using capacitive proximity sensing?
- RQ3: Can capacitive proximity sensing contribute to the acceptance of vehicular human machine interfaces with regard to privacy concerns?

Challenges that are present for research question RQ1 relate to vehicular human machine interfaces. The considered challenges are presented in Section 1.1.1. Just as the focus of research questions RQ1 to RQ2 changes from interfaces to interaction, we will also focus on the challenges for in-vehicle interaction in Section 1.1.2. Section 1.1.3 will present the analysis of privacy concerns about capacitive proximity sensing and selected sensors in established driver monitoring systems.

### 1.1.1. Challenges in vehicular human machine interfaces

Many systems deal with the issue of how to drive safely. There are passive safety systems such as airbags and seat belts that try to minimize the consequences of an accident [Nat19]. This thesis is dedicated to active safety systems. Systems that observe the physiological condition of the driver and passengers in vehicles are examined. There are systems that register the behavior of the driver. Systems in the literature capture, for example, behaviors that are considered irresponsible. They detect whether people smoke or eat while driving, as shown for example by Su et al. [SC19]. In contrast to these systems, this thesis focuses on driver and passenger state detection to improve driver and passenger safety. Two conditions are picked: driver attentiveness and child in child seat conditions. This selection relates directly to the research question RQ1. We will now elaborate on the issues of these two conditions and their connection to RQ1. Transporting a child in a child seat is the first condition considered. Securing children in a child seat is mandatory when traveling with children in vehicles. Child seats are primarily passive safety systems. So, they prevent injuries in the event of an accident. Using child seats solely as passive safety systems, without being able to use their structure for active safety systems or comfort systems, ignores many opportunities. Passive systems do not supervise children while driving. Children must be supervised even when driving alone. At the same time, the driver must also watch the road.

If children are left unattended in a child seat, this can lead to critical situations. Leaving a child in the vehicle can be accidental or intentional. Leaving children unattended in the vehicle can cause heat stroke. It happens to everyone that a child must be left unattended in the car. Although one may think, leaving a child in the car on purpose is not an option. There may be occasions when one has to act in an emergency to save lives. When one

arrives at an accident, one may have to make a decision. In such cases, one may choose to leave the child in the car because the conditions are fine for the child. Intentionally leaving children in vehicles can still pose a great danger to children [Nul19]. A system that monitors the condition of children in child seats while one has to leave the car would be very helpful. There are other situations in which injuries to children can occur unrecognized, even if there is no accident and the person responsible is riding in the car. Violent acceleration that remains undetected can lead to injuries [ESB*99]. A child seat capable of detecting critical acceleration could identify such situations. Even if children are not injured or left alone in the car, their condition may deteriorate unnoticed. Maintaining a good mood would be a comforting feature. It is the responsibility of those responsible to decide whether it is time for a break or time for a diaper change, for instance. This cannot always be guaranteed. For example, children entertained by a multimedia system may become anxious without being detected. Mood preservation, especially emotion assessment, could be inferred by physiological characteristics. In general, a system that addresses injury detection and mood maintenance can provide evidence for research question RQ1. Specifically, research question RQ1 is considered with a particular focus on vehicle structures that can provide information about the child's condition. The child seat is selected as a potential vehicle structure because the concept of existing vehicle structures includes temporary vehicle structures such as child seats. Thus, not only static vehicle structures that are already standard in vehicles are addressed.

Transporting children in vehicles is one aspect of using a car. As mentioned earlier, the next system of concern for research question RQ1 is a driver monitoring system. This is selected because cars must be used by at least one person: the driver. In fact, more than 74 percent of the total kilometers driven in Germany in 2017 were done by passenger cars. More than 54 percent of kilometers are driven by people as drivers [NKFB19]. Every time one has to drive, it is crucial that one's full attention is focused on the driving situation. Driver fatigue and inattention can lead to accidents. That's why driver fatigue and inattention are sensed by driver assistance systems. Although drowsiness cannot be measured directly, symptoms of drowsiness and inattention can be monitored. Symptoms such as suspicious eye movements, gazing, yawning, heart rate, nodding, and suspicious steering behavior are recognized by existing systems to evaluate drowsiness and inattention. In addition to safety monitoring while driving, initial adjustment of the driver's seat is important for safe driving. Systems such as headrests or backrests must be properly adjusted. People need to know when their seat is properly adjusted. Lack of information can lead to faulty operation, which poses a safety risk. An unobtrusive system must therefore be developed to assist in the adjustment of the backrest and headrest. In this case, research question RQ1 regarding the physiological and anthropometric conditions of the driver will be partially answered.

Having described the field of the two applications, we move on to the problems of current systems that attempt to solve problems in these fields. The first systems we discuss are child monitoring systems. Neglecting the limitation required in RQ1 to use capacitive proximity sensing, the research has already considered the selected domains of child monitoring and driver monitoring. Nevertheless, there are problems that have not yet been solved. Found research that addresses problems of children in vehicles mostly focuses on detecting the presence of children [CC19, DLT*16]. Child presence is detected, for example, by installing a sensor in the roof of the vehicle. This approach primarily helps to determine whether children are being left in the car unintentionally. The fact that children can be left behind intentionally is not taken into account in these systems. Vehicle manufacturers and the customer must also select a specific vehicle body to allow these sensors to be installed in the vehicle. The ubiquitous child seat is not used by these child presence detection systems as a basis for the sensors. Instead of sensors in the child seat, cameras are used for instance by Yoon et al. [YKE04] to detect the orientation of the child seat. Privacy concerns may therefore arise if, for example, facial images are captured. Monitoring the physiological state of the child is also neglected in current systems. In addition to research on child seats, research is also being undertaken on various functions that support the driver. One function is seat adjustment, which has already been described. In terms of seat adjustment, for example, researchers have used pressure mats that are built into car seats [Rie10]. This also enables them to identify people on the seat. This sensor setup is

even supported by a capacitive proximity sensor in the headrest, as shown by Lorenz [Lor11]. These systems are therefore not only based on capacitive proximity sensing. Pressure sensors necessitate contact between the object and the car seat. In addition to seat adjustment, detection of attention or fatigue is also important for safe driving. Researchers are using a variety of sensors to detect physiological characteristics that indicate driver alertness. Depth cameras detect gaze, pulse sensors measure the driver's heart rate, and sensors measure the angular displacement of the steering wheel [LWC*14]. These sensors are not only included in the driver's seat. While a variety of sensors are used in these systems, we will utilize only one kind of sensor: capacitive proximity sensing.

These issues, how to secure children in child seats and how to monitor the driver while driving, were selected to demonstrate several problems related to research question RQ1. Human machine interfaces, in particular, are designed to solve existing problems. In this case, the problems to answer RQ1 would need to be solved using capacitive proximity sensing and an existing vehicle structure. Evidence of how to solve RQ1 must be found by designing appropriate algorithms that measure required symptoms and human emissions that must be integrated into vehicle structure prototypes, so that the designed systems can be evaluated. A concept of how this can be done is presented in Chapter 3.

### 1.1.2. Challenges in vehicular human machine interaction

Issues of driver and passenger monitoring systems that could be addressed by using existing vehicle structures with capacitive proximity sensing are presented in Section 1.1.1, so research question RQ1 is now covered. We shift the focus from human machine interfaces without interaction to those with interaction to address research question RQ2. The investigation of issues related to RQ2 is divided into two parts. Driver authentication issues and required interaction are addressed in the first part. Interaction for gesture recognition, including deictic and symbolic gestures, is addressed in the second part. We start with issues of interaction between the user and the system regarding identification and authentication. Identification and authentication systems can function without interaction (e.g., facial recognition). Issues of authentication in vehicles may therefore also interfere with RQ1. Mechanisms that require user interaction are nevertheless specifically singled out and presented.

Authentication is required to grant access to a system only to authorized persons. For example, not everyone owns a car. That is why authentication is required for car sharing. Cars can also be shared among people in companies. In both cases, frequent driver changes are the result. Drivers must be verified and distinguished from each other. Comfort functions such as automatic multimedia adjustment for authenticated drivers can also be set. Automakers build in memory functions to adjust vehicles to specific drivers. If drivers cannot be distinguished by the system, system functions must be set manually by the driver each time the vehicle is changed. So, using a vehicle with many drivers can be cumbersome. Functions such as the memory function can only be selected if the driver has already been authenticated. Reliable authentication mechanisms are therefore compulsory. There are plenty of different physical methods to validate the driver's identity. Most often, manufacturers rely on physical keys that provide a radio link to communicate for authentication. The driver's key is therefore often the only instance of authentication, but this physical device can grant access to unauthorized drivers if it is lost. The same is true for other physical entity bond systems such as authentication cards. If the driver's key is extended to a keyless go system, this system is even vulnerable to remote attacks [GOKP16].

The problem that authentication based on physical systems can be lost or give access to unauthorized drivers is tackled by other authentication mechanisms. Fingerprint sensors, for example, are being installed in vehicles [SMG*04]. The fingerprint appears to be a reliable system for authentication. In this case, the authentication mechanism cannot be lost and is tied to a unique, personal characteristic. However, this also brings problems. A person is bound to her or his biometric data. If this data is captured by thirds, the authentication mechanism

is insecure [Fin19]. The authentication process cannot simply be changed if biometric data has been leaked to a third party. The immutability of biometric data is addressed by a different authentication mechanism. Systems with changeable keys solve the problem of immutable biometric data. In this case, a password or pattern is provided by the user. An example of mutable keys are touch-based authentication systems such as screen unlock patterns. Research has shown that these systems are already vulnerable. Patterns can be guessed based on the residue of the finger on the screen, which is created by the contact between the screen and the fingers [AGM*10]. Another problem is that the fingerprint sensors and touch-based authentication have to be integrated into the vehicle interior design. This means they cannot be integrated invisibly into existing vehicle structures.

We have discussed various problems of authentication so far. In particular, authentication is considered as a form of human machine interaction in vehicles. The problems of authentication are selected to address the research question RQ2. For research question RQ2, we investigate whether an authentication system based on capacitive proximity sensing can be invisibly integrated into an existing vehicle structure to address the problems. We will see in Chapter 5 that capacitive proximity sensors can be used even with the constraints that have arisen, so that an existing authentication mechanism can be enhanced or replaced with an improved authentication process. After discussing interaction issues for authentication systems in vehicles, research question RQ2 is addressed by one system so far. A variety of interaction applications exist in the field of human-computer interaction in vehicles. To increase the diversity of this thesis and further address research question RQ2, another domain is selected: gesture recognition. Issues related to RQ2 that point to the use of human computer interaction as a control system for the vehicle are the next research area considered. Gesture interaction in the vehicle itself is already a system that attempts to address human machine interaction problems in vehicles, such as distraction. As already discussed in Section 1.1.1, distracted driving can lead to dangerous situations that increase the risk of accidents significantly. According to the NHTSA [NHT20b], eight percent of all lethal crashes in 2018 in the United States were caused by distracted drivers. With the help of gesture recognition, the driver is expected to keep his or her eyes on the road even if she or he changes the setting of, for example, the multimedia system. The use of gesture control could therefore reduce the driver's distraction [GGK19].

In addition to gesture recognition, driver distraction is being addressed by other devices in the vehicle. Distraction is expected to be reduced through the use of head-up displays. When these systems are installed, it is expected that the driver will be able to look at the road for longer periods of time instead of looking at instruments in order to gather information [APW*07]. A head-up display is a device that can display information in the line of sight between the driver's eyes and the road. This means drivers do not have to look away when they need information. Many head-up displays provide static information, but the information provided by head-up displays today is no longer static. So-called augmented head-up displays have emerged. Augmented head-up displays can display live data of driving situations in the driver's line of sight. For example, navigation commands can be displayed and adapted to the driving situation, or distances to vehicles ahead can be displayed [GTFC12]. The advantages of gesture recognition and head-up displays can be combined. Head-up displays are in fact already being combined with gesture control, for example by Lagoo et al. [LCH19], but the focus of these systems is on symbolic gestures. A more natural interaction could reduce distraction and provide extended gestures that match the driving situation. Many gesture recognition systems are based on infrared sensing or cameras. The problem is that these systems rely on a line of sight between the driver and the sensor position. They therefore need to be integrated into the design of interfaces. Cameras can also cause privacy issues, as they could capture facial images.

Until now, we have focused on hand gestures combined with another system so that driver distraction can be tackled. Many vehicle manufacturers are focusing on hand-based gestures. I have found few systems that use the driver's feet to interact. This may be counter-intuitive, since gestures in common human communication are often based on hand gestures, but feet are part of body language. People use their feet to express feelings such as impatience, insecurity, or boredom [Sie79]. Acceleration and operating the clutch are the main tasks in vehicles

that require the driver's feet. These tasks are already automated by cruise control and automatic shifting, so the driver's feet are idle in many driving situations. Drivers could benefit by relieving the strain on their already busy hands, which are used for steering, multimedia operation and gestures. Thus, the driver's idle feet could be used for interaction. Some researchers like Tran et al. [TDT12] already recognized the potential of feet gestures for pedal usage prediction. Similar to many hand gesture recognition systems, Tran et al. use a camera. This may cause privacy issues. Nonetheless, monitoring the driver's feet may cause fewer privacy issues than the possible capture of facial images. However, the presented camera-based system has other weaknesses. A line of sight is required for camera-based systems, but a line of sight within the legroom is not always given. A skirt, for example, can obscure the driver's feet and legs.

### 1.1.3. Privacy preservation and the user's voice

So far, we have analyzed the specific problems associated with research questions RQ1 and RQ2. These questions primarily address technical issues for human machine interfaces in vehicles. Privacy preserving behavior is demanded in all considered applications of Section 1.1.1 and Section 1.1.2. Both research questions are therefore part of research question RQ3. RQ3 is about privacy-preserving systems. RQ3 specifically addresses how capacitive proximity sensing can reduce privacy concerns towards vehicular human machine interfaces, increasing the adoption of those systems. Privacy and data protection concerns play a major role in our daily lives. The law, on the one hand, enforces rules for privacy-compliant behavior. The subjective perception of privacy, on the other hand, influences our behavior [FR16]. Law and personal perception can differ. Two perspectives are therefore considered for research question RQ3. First, research question RQ3 will be answered in terms of the law. Issues related to legislation for human machine interfaces in vehicles are presented in Section 1.1.3. Second, RQ3 addresses users' personal feelings about privacy with respect to human machine interfaces in vehicles.

We start with questions concerning the perspective of law. Especially since the advent of data collection services in automotive applications, the regulatory definition of privacy-compliant behavior has influenced the design of driver assistance systems. One regulation is the European Union's General Data Protection Regulation (GDPR) [Cou16]. The European Union demands compliance with data protection. In particular, articles such as, "Data Protection by Design and Data Protection by Default", of the GDPR can have an impact on the design of driver assistance systems. The use of sensors for driver assistance systems, which can collect various types of data, is particularly affected. Many sensors in vehicles collect personal data. Due to privacy by design, these systems must be examined for compliance. It is questionable whether a camera-based human machine interface collects only the information it needs. Especially if the goal of the system is to capture hand gestures while simultaneously capturing images of the entire driver's body. Researchers like Walter et al. [WAP*17] try to minimize communication between in-vehicle systems and keep sensors as they are. This relies on secure software. Hardware-based systems, like capacitive proximity sensing, could rule out security gaps right from the start. Yet, the privacy preserving features of capacitive proximity sensing are stated but not checked.

In addition to new legal regulations on the protection of personal data, people themselves are also becoming increasingly sensitive to their own data protection concerns. This is for example shown by Kroschke [Kro18] concerning the willingness of people to disclose personal information in the internet. Systems that capture personal data may raise privacy concerns. Systems that require a camera to provide functions may capture personal data such as facial images. Sensitivity to the disclosure of personal data could be heightened, especially if similar systems could be deployed with a sensor that is considered less of a privacy concern. Researchers like Bloom et al. [BTRB17] investigated personal privacy concerns towards connected vehicles. This research does not include specific sensor systems. A direct comparison between camera-based systems and other sensors, especially capacitive proximity sensing, is not yet available. In addition to privacy awareness, people are sometimes unaware that other sensor systems can be used for the same tasks in assistance systems. If they can be made aware of

this, perhaps they would think about the sensor choices made by vehicle manufacturers. People should be asked about their preferences when they need to select a sensor system based on their subjective privacy concerns.

In summary, two different types of issues are presented here to answer research question RQ3. The first part is about regulations, especially the GDPR of the European Union. To provide evidence for research question RQ3, the conformity of existing sensor systems, and in particular capacitive proximity sensing, with the GDPR should be evaluated. Since vehicle users' personal feelings about privacy are not necessarily reflected by regulations, research question RQ3 also requires collecting vehicle users' personal opinions about sensor systems and privacy in vehicles. The evidence collected for both perspectives will serve as a basis for asking whether capacitive proximity sensors in vehicles can improve privacy compared to other systems with similar capabilities, thereby improving the acceptance of human machine interfaces in vehicles. In Section 1.2, steps of how the problems concerning RQ1, RQ2 and RQ3 are tackled in this thesis are introduced.

## 1.2. Contributions

We discussed several challenges for vehicular human machine interfaces in Section 1.1.1, Section 1.1.2 and Section 1.1.3. It is shown how these challenges relate to the research questions RQ1, RQ2 and RQ3. RQ1, in particular, addresses the question of how an existing vehicle structure can be equipped with capacitive proximity sensing so that in-vehicle human machine interfaces can be improved or replaced. Research question RQ2 narrows the domain of human machine interfaces to interaction. Thus, research questions RQ1 and RQ2 aim to develop human machine interfaces and enable human machine interaction in vehicles. Although this could be evaluated by mere applications with capacitive proximity sensors in vehicles, evidence for the issues should be found by significant applications that address real problems of drivers and passengers. Therefore, the application of capacitive proximity sensors must be developed with care. Even if capacitive proximity sensors can do the job, they may not be the best choice. To evaluate the choice, existing frameworks for developing applications with capacitive proximity sensors are examined. Braun [Bra14] provides a benchmarking model in his dissertation. This model is described briefly in Chapter 2. While this model is aimed at evaluating sensors for applications in general, we will apply it to vehicle-based systems. In addition, we incorporate the benchmarking model into a process that helps develop and evaluate capacitive proximity sensing-based applications in vehicles, under the constraint of using only existing vehicle structures.

The process that is applied for research question RQ1 is visualized in Figure 1.2. Each step of the process is numbered from one to eleven. The preliminary judgment of whether this is feasible with capacitive proximity sensing in step six depends on the researcher's knowledge of the physical background and related work. Step five is therefore placed at the top of the decision-making processes, as an understanding of the physical properties and investigation of related work should support the feasibility decision. Portions of step five may also be partially included in step one: Existing Systems, Research, and Statistics. In particular, already manufactured in-vehicle systems are also included in step one. This does not only include interaction devices. This can also refer to devices such as head-up displays that do not show interaction but can provide opportunities for interaction. The complete process is presented in this paper. It is applied to selected application ideas. To give an indication of the process, several examples are now presented. These examples refer to the developed devices.

As mentioned earlier, the goal of this thesis is to demonstrate and evaluate possibilities of capacitive proximity sensors in vehicles. These sensors are considered privacy-friendly, unobtrusive, have a low impact on design and enable new ways to monitor individuals. Exemplary entities for problems, opportunities, and sensors of existing systems and related work are shown in Figure 1.3. Steps one to four of Figure 1.2 are therefore covered. All mentioned features refer to found problems or entities in projects of this thesis related to existing human machine interfaces in vehicles. Related problems are collected to be addressed by these systems. Each problem relates

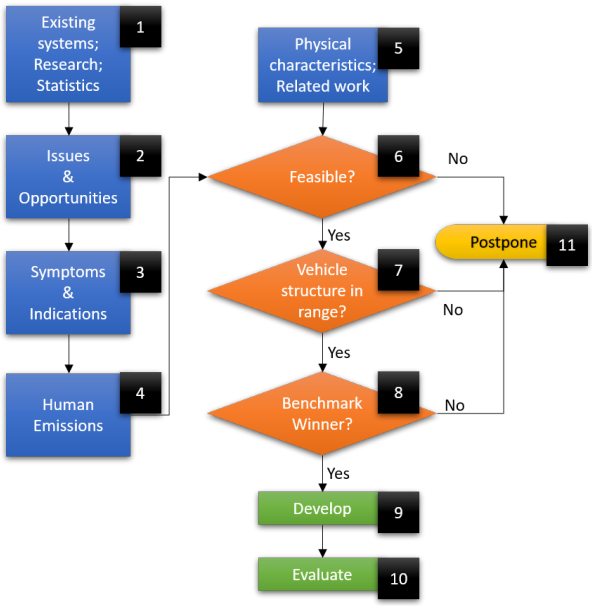



Figure 1.2.: Approach summary: from idea to evaluation

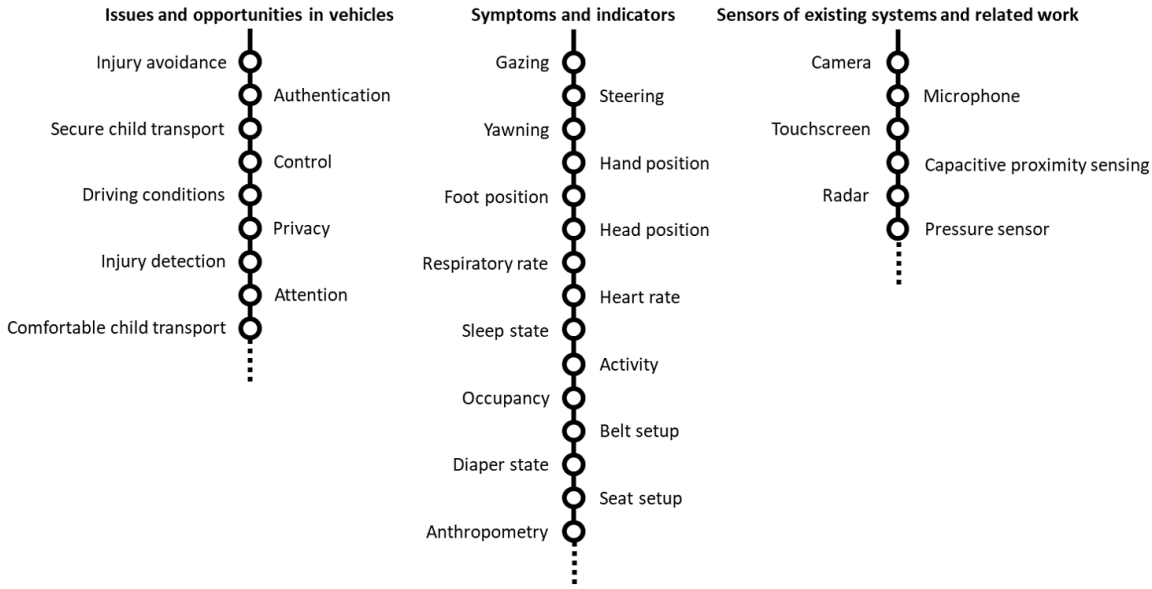



Figure 1.3.: Approach part 1: gathering of issues, opportunities and existing systems

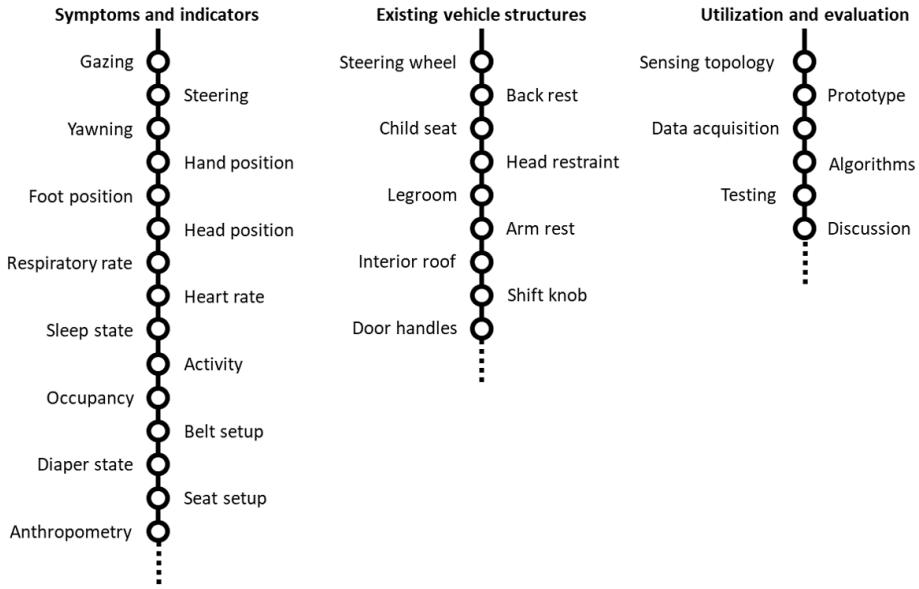



Figure 1.4.: Approach part 2: utilization of existing vehicle structures

to symptoms and indications of the human body that can be detected using capacitive proximity sensing. The second part of the approach is shown in Figure 1.4. Steps six, seven, nine and ten of the process shown in Figure 1.2 are therefore covered. Due to the physical properties of capacitive proximity sensing, symptoms related to body movement could be detected with these sensors. Because of the limited range, an existing vehicle structure must be found that is close to the body part showing the symptoms. The selection of appropriate symptoms is enhanced by applications with capacitive proximity sensing in related work (Figure 1.2, step five). Even if a vehicle structure has not yet been used with capacitive proximity sensing, there may be similar applications in the non-automotive sector.

After required symptoms, indicators and an existing vehicle structure are found, the concept for the system has to be defined. This is enabled by a benchmark check in step eight of the process, which is shown in Figure 1.2. The benchmarking is necessary to be able to evaluate the significance of the development of a system equipped with capacitive proximity switches in comparison to other sensor systems. If the verdict of the benchmarking is positive for capacitive proximity sensors, one can proceed to the development of the actual system in step nine. In this step, the vehicle structure must be equipped with a suitable sensor topology. A processing algorithm must be designed that can enable the required functions based on this topology. The developed algorithms and the entire system must also be tested. A prototype must therefore be built to implement the design. The prototype is used, in particular, to collect data under laboratory or real-world conditions. The approach is completed by evaluating the algorithms found and a discussion of the results in step ten. A detailed description of the approach to answer research questions RQ1 and RQ2 is presented in Section 3.1.

Section 1.1.1 named several domains of vehicular human machine interfaces which are yet undiscovered or show issues that could be enabled with alternative sensing systems as capacitive proximity sensing. Each considered domain and proposed solutions are introduced in Section 1.2.1. Focus is moved from interfaces to interaction

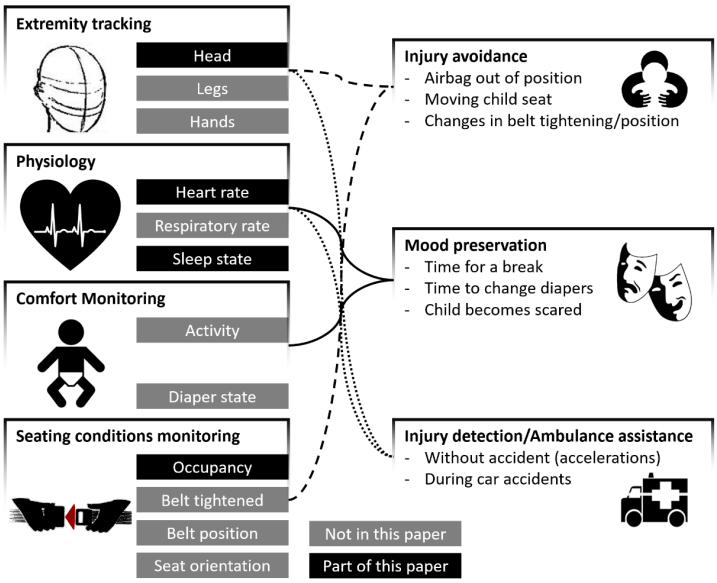



Figure 1.5.: Considered concepts for child monitoring [FK20a]

in the challenges presented in Section 1.1.2. Similarly, contributions to interaction are presented in Section 1.2.2. Privacy concerns relate to all issues and address research question RQ3. Contributions to this topic are introduced in Section 1.2.3. Before we can begin to introduce the specific applications of this thesis, a brief summary of the characteristics of capacitive proximity sensing is necessary to understand the actual advantages of the sensor system and why they are chosen. Capacitive proximity sensors have the ability to measure changes in the electric field. Changes in the environment can affect the electric field. These changes can be caused by people approaching the sensor. Because these sensors can measure through non-conductive material, they can be placed under vehicle upholstery, coatings, and covers. A detailed description of how capacitive proximity sensors work is presented in Section 2.1.2.

### 1.2.1. Vehicular human machine interfaces

Two domains are considered for vehicular human machine interfaces. In particular, challenges for driver monitoring and child transport in vehicles were presented in Section 1.1.1. We begin with the safe transportation of children in vehicles. Contributions in this field are related to publication *NannyCaps – Monitoring Child Conditions and Activity in Automotive Applications Using Capacitive Proximity Sensing* [FK20a], which I co-authored. Three areas are identified to help parents transport their children safely. Each area is shown on the right in Figure 1.5. Injury avoidance measures changes in the child's seating conditions. In addition, injury prevention includes the detection of dangerous head positions that could overlap with the deployment ranges of airbags (out-of-position). Latest child seats [Max20] include airbags within the child seat structure. Similar to ordinary driver and passenger airbags, overlap between the subject's head and the deployment area of the airbags could result in injury. An appropriate head tracking system could detect out-of-position situations. Capacitive proximity sensing is to be used to detect the head position. Issues concerning children left behind in vehicles are furthermore already tackled by researchers like Diewald et al. [DLT*16] by use of child presence detection systems. This can

prevent injuries such as heat stroke. Unlike existing occupancy detection systems, capacitive proximity sensing is only integrated into the structure of the child seat. The system is therefore independent of additional vehicle structures such as the interior roof. Additional features turn the passive child seat safety system into an active safety system with comfort functions. Maintaining the child's mood can be enabled. For example, features such as heart rate detection, activity detection, and diaper condition can enable comfort functions. In this thesis, an ordinary child seat is equipped with capacitive proximity sensors. Described functions are implemented using machine learning processing models. The system is additionally tested under real conditions in test runs with a test person. The application of the concept of this thesis, the development of the system and the evaluation are presented in Section 4.2.

Apart from the safety provided by child seats, monitoring the proper constitution of the driver is the second domain considered for human machine interfaces in vehicles. Contributions in this field are based on publication *CapSeat: Capacitive Proximity Sensing for Automotive Activity Recognition* [BFMW15] and my master's thesis *Capacitive Proximity Sensing Supported Advanced Driver Assistance System* [Fra14], which I co-authored. As introduced in Section 1.1.1, this may be enabled with a proper initial seat setup. Another point is that tired drivers should not drive. A system that monitors the driver's attention is therefore required. Attention monitoring, in particular, can be based on cameras, but since these can raise privacy concerns and require a line of sight, which affects interior design, capacitive proximity sensing is chosen as an alternative system. These sensors are invisibly integrated into the driver's seat. Based on this design, various symptoms of driver fatigue can be derived using specific processing methods. In particular, the detected symptoms are yawning, nodding, gazing, and suspicious steering behavior. The same sensor setup is used to estimate the driver's dimensions and support proper seat adjustment. As with the child seat, the concept of this thesis is applied to the driver's seat equipped with capacitive proximity sensors. An ordinary driver's seat is used. The designed algorithms are tested in a user study with six participants on the prototype. Due to the circumstances of the user study, the function of the system is tested under laboratory conditions. The detailed approach for developing the driver's seat equipped with capacitive proximity sensing that measures symptoms of inattention and driver's body dimensions for assisted adjustment is presented in Section 4.1 of Chapter 4.

### 1.2.2. Vehicular human machine interaction

Besides challenges for vehicular human machine interfaces, challenges for vehicular human machine interaction are discussed in Section 1.1.2. The first considered domain for interaction is authentication. Contributions in this field are related to publication *AuthentiCap – A Touchless Vehicle Authentication and Personalization System* [FK17a], which I co-authored. As described in Section 1.1.2, an authentication process for vehicles is to be discovered. The process must not be based on a portable device such as keys, as these can be stolen or lost. Biometric data should also not be used, as this data cannot be changed. It should be contact-less to prevent guessing password patterns from fingerprints. These constraints are met by using capacitive proximity sensors. In this thesis, an array of capacitive proximity sensors is incorporated into a vehicle steering wheel. This allows the area around the steering wheel to be monitored. The hands in the area around the steering wheel are therefore included. A processing algorithm that tracks the driver's hand movements is defined for this purpose. The driver can write with his or her hand in the free air. This allows the driver to set up password-like gestures without touching any surfaces. Drivers can change the password and no data causing privacy concerns, such as their face, is captured. This system is being tested with five participants under laboratory conditions. The complete design and development process is shown in Section 5.1 of Chapter 5.

In this thesis, another interaction device based on hand interaction is contributed. Almost the same mechanical setup that enables driver authentication can in fact be used to enable a new type of gesture interaction. The ability to insert a computer-mouse-like cursor into a head-up display to perform deictic gestures is provided.

Contributions in this field are related to publication *HUDConCap – Automotive Head-Up Display Controlled with Capacitive Proximity Sensing* [FK17b], which I co-authored. Due to this setup, the issues shown in Section 1.1.2 can be tackled. The driver's hand movement is translated directly into a cursor position by the proposed solution. Invisibly integrated sensing electrodes in the steering wheel are used as the basis for the system. The whole system is tested under laboratory conditions with six test subjects. A detailed description of the development of this system is presented in Section 5.2 of Chapter 5.

Previously contributed interaction devices such as the authentication systems or the head-up display cursor rely on hand interaction. In fact, the driver's hands are the focus of many gesture recognition systems. As described in Section 1.1.2, only few researchers recognize the driver's feet as observable entity in vehicles. This body part, which is already made inactive by systems such as cruise control, can be used in a gesture recognition scenario. To enable tracking of the feet, the vehicle's leg compartment is equipped with capacitive proximity sensors under the floor mat. The system is thus invisible. This setup is used to design a method that distinguishes between four different foot gestures. The designed application is tested under laboratory conditions with six subjects. A detailed description of the development of this system can be found in Section 5.3 of Chapter 5. Contributions in this field are related to publications *Robust driver foot tracking and foot gesture recognition using capacitive proximity sensing* [FK19] and *Enabling Driver Feet Gestures Using Capacitive Proximity Sensing* [FK18], which I co-authored.

### 1.2.3. Privacy preservation and the user's voice

The property that capacitive proximity sensors protect privacy is an untested attribute to date. This attribute is named especially in comparison to camera-based systems. Privacy concerns are part of the law, and people have a subjective privacy perception towards systems. Because of this condition, the privacy analysis is split into two perspectives. On one hand, the interference between existing human machine interfaces in vehicles and the law is analyzed. Contributions in this field are related to publication *Privacy by Design: Analysis of Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces* [FK20b], which I co-authored. On the other hand, the subjective feeling of people towards human machine interfaces in vehicles is captured. Contributions in this field are related to publication *Privacy by Design: Survey on Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces* [FK20c], which I also co-authored.

The encroachment of the law can be seen through jurisdiction. Laws designed to protect user privacy, such as the European Union's General Data Protection Regulation [Cou16], have specific definitions of privacy. Existing in-vehicle human machine interfaces can be examined to determine whether they conflict with these definitions. It is examined whether in-vehicle human machine interfaces that rely on similar sensor systems provide additional information that may raise privacy concerns. Even though this analysis is based on a law-based analysis, three hypotheses are derived to identify human privacy concerns about camera-based systems and systems using capacitive proximity sensing. The detailed analysis of the compliance of existing systems with privacy by design is shown in Section 6.1.

This analysis can capture concerns about existing laws, but does not reflect people's subjective feelings about these systems. A survey therefore asks participants to rate camera-based human machine interfaces in vehicles and those based on capacitive proximity sensors in terms of their perceptions of privacy. The survey aims to explore three hypotheses about people's privacy concerns about human machine interfaces in vehicles. The hypotheses are specifically tested using an online questionnaire that is designed and distributed while working on this thesis. In total, more than 300 participants are collected. More than 250 participants belong to the target group and thus to German drivers. The details of the survey are presented in Section 6.2.

## 1.3. Structure of this thesis

The research questions emerged from the analysis of related work in which researchers are also working on similar issues. Open questions and problems of existing systems that have not been discovered and answered by other researchers are the basis of this thesis. Many functions enabled by capacitive proximity sensing are part of the research. In addition, research that has already been conducted, such as privacy in connected autonomous vehicles, is the basis for investigating the use of capacitive proximity sensors. Before related research can be investigated, the physical properties of capacitive proximity sensing must be known. Relevant literature required to understand how capacitive proximity sensing can help or introduce new ways of human machine interface in vehicles is shown in Chapter 2. In order to understand the advantages and disadvantages of capacitive proximity sensors, they are introduced in Section 2.1 of Chapter 2. The origin, physical background, and in-vehicle and off-vehicle applications are explained here. How researchers have already addressed symptoms and indications for in-vehicle human machine interfaces is discussed in Section 2.2 of Chapter 2. New approaches for in-vehicle systems based on capacitive proximity sensors can be derived from these applications. The advantages and disadvantages resulting from the use of capacitive proximity sensors relate to the physical background presented in Section 2.1.2. Capacitive proximity sensing, for example, is considered privacy-preserving. To verify this, an overview regarding related works on privacy is needed. Therefore, related work on privacy preservation is shown in Section 2.4 of Chapter 2 that forms the basis for the evaluation of privacy preserving features of capacitive proximity sensing in this thesis. The content of Chapter 2 is summarized in Section 2.5. The summary includes an overview of which problems have not been solved by related work.

Chapter 2 is required to move over to Chapter 3: the concept. The concept describes how we can modify models of related work to form a new process for answering research questions RQ1 and RQ2. The new process is already shown in Figure 1.2. In Chapter 3, we add details to the processing steps. In particular, the specific implementations shown in Chapter 4 and Chapter 5 are prepared in Chapter 3. Privacy concerns caused by sensor systems can take influence on the process of Figure 1.2. Research question RQ3 is thus addressed. Assessment of privacy in relation to the law and people's perceptions, however, is not represented by this process. An approach to assess vehicle users' privacy and regulatory concerns is shown in Chapter 3.

The concepts found in Chapter 3 must be applied to find evidence for the research questions. Several applications are implemented in Chapter 4 and Chapter 5. These applications take place in the area of human machine interfaces and interaction in vehicles. The results of these applications, which follow the development process shown in Figure 1.2, provide clues to research questions RQ1 and RQ2. RQ1 is mainly addressed by Chapter 4, while RQ2 related applications are developed in Chapter 5. Chapter 6 is different, because it does not show a technical implementation of a human machine interface. It shows the implementation of a survey to capture people's privacy concerns about certain vehicle sensing technologies to provide guidance for research question RQ3 regarding the user's perspective. The analysis of existing vehicular human machine interfaces concerning privacy by design and regulations is also shown in Chapter 6.

The results of this thesis are summarized in Chapter 7. It will be shown in particular how the concept found for the development of in-vehicle human machine interfaces and interactions was applied to the applications of this thesis. The relation to the research questions is elaborated and the overall domain of the research questions is shown. The research questions are then recapitulated and placed in the higher-level domain. Unanswered questions in the overarching domain or new questions are thus presented. Each contribution chapter is then discussed. The respective results are presented and the discussion is briefly summarized. As mentioned before, the research questions cannot be answered completely. Open-ended questions and the revealed answers are therefore presented with limitations. These open questions lead to the ideas for future work that are also presented.

# 2. Related work

As shown in Chapter 1, this thesis is about capacitive proximity sensing for human machine interfaces and interaction in vehicles. Three research questions related to human machine interfaces and interactions in vehicles are to be examined. Before embarking on the path to answering these research questions, existing frameworks and applications for human machine interfaces must be explored. Since capacitive proximity sensors are the basis for interfaces and interaction in this thesis, the physical background and operation of capacitive proximity sensors must be recapitulated before existing applications of related work can be presented.

Due to the physical properties of capacitive proximity sensors, they can enable new ways of human machine interface in vehicles. To understand these characteristics, the required physical background is shown in Section 2.1. An introduction to the history of capacitive proximity sensing is additionally given in Section 2.1. Since researchers are also working on capacitive proximity sensing outside the automotive field and their work has an impact on the applications of capacitive proximity sensing in vehicles, Section 2.1 presents vehicle-related and non-vehicle-related applications. Different materials and geometries are used in vehicle interiors. Sensor topology and setup must therefore be adapted. The research on materials for capacitive proximity sensing is presented in Section 2.1. Of course, we also take a look at applications of capacitive proximity sensing in vehicles. Applications that monitor drivers and passengers in vehicles are shown in Section 2.2. Other systems that do not rely on capacitive proximity sensing are shown in Section 2.2. These systems nevertheless overlap with this thesis in that they provide similar symptom and indication measurements as capacitive proximity sensing. These systems, in particular, are driver or passenger monitoring systems, authentication systems, and gesture control systems, that rely on a variety of sensors. An assessment on use of sensors would be helpful. Such a benchmarking process is shown in Section 2.3. Section 2.3 is required to prepare the concept for the development of human machine interfaces and interactions based on capacitive proximity sensing in this thesis.

Sensor systems other than capacitive proximity sensing have specific advantages and disadvantages over capacitive proximity sensing. One attribute often cited for capacitive proximity sensing is that it is privacy compliant. This will be examined in this thesis. Related work that addresses privacy-friendly attributes or privacy-relevant conditions in vehicular applications is presented in Section 2.4. In addition, European Union regulations that may influence the design of human machine interfaces are presented here. How related work partially answers or substantiates research question RQ3 is therefore addressed in Section 2.4. Chapter 2 is then concluded by a summary in Section 2.5, which provides an overview of the related work presented and addresses unresolved issues.

## 2.1. Capacitive proximity sensing

A basic understanding of capacitive proximity sensing is necessary to understand decisions for specific applications and how to address research questions. To get to the origins of capacitive proximity sensing, Section 2.1.1 presents the evolution of this sensor technology from its use in a musical instrument to its application in cell phones and in industrial environments as a proximity switch. In order to recognize the manifold applications, one must be aware of the basic physics. The required physical background for capacitive proximity sensing is shown in Section 2.1.2. Since this thesis deals with the development of human machine interfaces based on

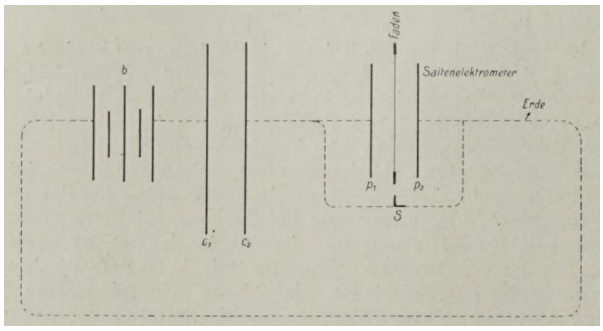



Figure 2.1.: Experiment of Cremer (without frog heart) [Cre07]

capacitive proximity sensing, related research on various applications is shown in Section 2.1.4. Applications presented show how researchers addressed research questions RQ1 and RQ2.

### 2.1.1. History

Traditionally, a review of capacitive proximity sensing starts with Leon Theremin [Gli00] and his music instrument based on electric field sensing. Puppendahl [GP15] showed, first investigations concerning capacitive proximity sensing already took place in 1907. It was the researcher Cremer [Cre07] who recognized these effects in an experiment. Because of the close relation to the physical background, the experiment will now be briefly presented. The experiment setup is shown in Figure 2.1. The experiment consists of a power source (b) and a plate capacitor with two plates $c_1$ and $c_2$. A string galvanometer is connected in series, which can be short-circuited. The string is labeled with "Faden" and ground is labeled with "Erde". The string is between two plates ($p_1$ and $p_2$). At first, the string galvanometer is short circuited using the valve marked as "S". Cremer proposes an exemplary battery voltage of 1,000 V. After the capacitor with the plates $c_1$ and $c_2$ is charged, the valve at "S" is switched. Thus, the string remains in an equilibrium position. He then recognized that a beating frog heart, placed between $c_1$ and $c_2$ without touching the plates effects an oscillation of the string. The effect why this is measurable is shown in Section 2.1.2.

Even though Leon Theremin [Gli00] is not named in this paper as the discoverer of the capacitive proximity sensing principle, he did realize the first applications of capacitive proximity sensing. By using his body, he was able to manipulate the pitch and volume that a theremin produces. The theremin is his invention. It consists of two sensing electrodes. The electric field that is built up can be influenced by body movements. The fact that one can modulate the sound of music with the hands without mechanically touching an instrument already demonstrated the ability to measure gestures. How Theremin plays his instrument is shown twice in Figure 2.2

### 2.1.2. Required physical background

We saw in Section 2.1.1 that researchers encountered physical effects of capacitive proximity sensing as early as the early 20th century. Now we will discuss the physical properties that are needed as a basis for the subsequent applications and considerations in this thesis. As already indicated in the name of capacitive proximity sensing, the mode of operation is related to the physical properties of capacitors. A capacitive proximity sensor consists of a sensing electrode, e.g., a copper plate, and a processing unit. A capacitor is established with the environment

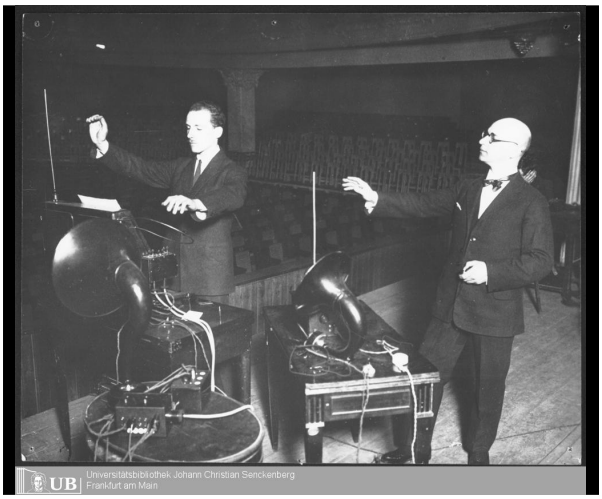



Figure 2.2.: Double portrait playing on the Theremin he invented [Fra03]

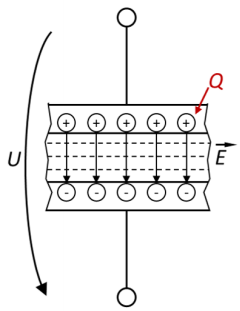



Figure 2.3.: Cross section through the inside of a plate capacitor

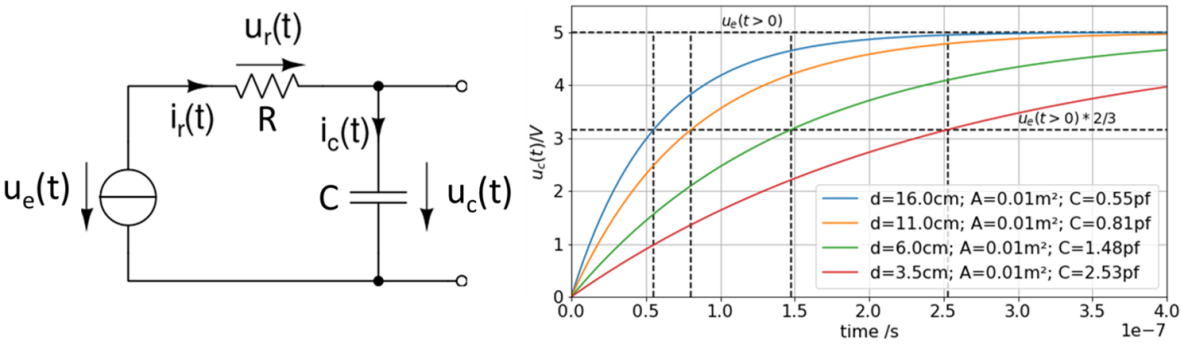



Figure 2.4.: Resistor with capacitor in an electric circuit $u_e(t < 0) = 0$, $u_r(t >= 0) = 5V$

through the sensing electrode. A capacitor is an electrical element capable of storing energy. While any electrical entity has a capacitance, focus in Section 2.1.2 is set on plate capacitors. As shown in Figure 2.3, a plate capacitor consists of two conductive plates. These are also referred to as electrodes. Between the two plates there is a medium, e.g., air. It influences the most important parameter of capacitors: the capacitance. Using the following equations, taken from Hagmann [Hag09], the relationship between the output of capacitive proximity sensing and the distance to nearby objects is explained, based on the properties of plate capacitors. When an electric potential ($U$) is applied between the two plates, the capacitor becomes electrically charged ($Q$). The charge is proportional to the potential: $Q \propto U$. This condition can be converted into an equation. A constant is needed. The constant is called capacitance ($C$). It is a measure of the capacitor's ability to store electric charge. The resulting condition is shown in Equation 2.1.

$$Q = CU \tag{2.1}$$

The capacitance of a plate capacitor depends on its effective area ($A$), the distance ($d$) between both plates, and the permittivity ($\varepsilon$). Equation 2.2 shows the relationship between these four quantities. Permittivity varies from material to material. It can be constant as in case of water ($\varepsilon = 81$) or can vary as in case of Barium Titanate ($\varepsilon > 1,000$). The permittivity of air is $\varepsilon = 1.0006$. The characteristic permittivity of materials will be discussed later in Section 2.1.2. For understanding, we need the information that when a potential is applied to a capacitor, the current detected ($I$) depends on the capacitance and the time derivative ($t$) of the potential. The relationship is shown in Equation 2.3.

$$C = \varepsilon \frac{A}{d}; \text{ and therefore } C \propto \frac{1}{d} \tag{2.2}$$

$$I = C\frac{dU}{dt}; \text{ and } U = \frac{1}{C}\int i\,dt \tag{2.3}$$

Before we continue with the properties $d$ and $A$, the capacitor is placed in a simple circuit with a resistor and a voltage source for simulation. The circuit is shown on the left of Figure 2.4. The voltage source $u_e$ is set to $0V$ at $t < 0s$ and to $5V$ at $t >= 0s$. Resistor $R$ is set to 100,000Ω. The capacitor is a plate capacitor with air between its plates. The area of the capacitor is $0.01m^2$. The distance between the plates is a variable which is set to the values 16cm, 11cm, 6cm and 3.5cm. The voltage $u_c(t)$ is the voltage at the capacitor $C$. The diagram of the voltage

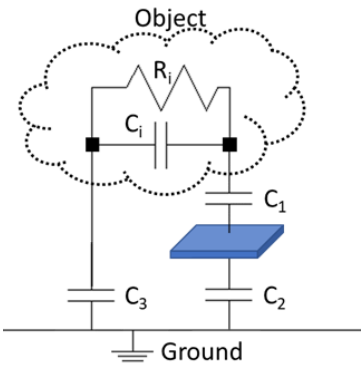



Figure 2.5.: Circuit model for electric field sensing, based on [SG99]

with the progression over time is shown on the right of Figure 2.4. The greater the distance, the lesser is the capacitance. According to Equation 2.3, the course of $u_c$ becomes steeper. A constant that describes the course of the voltage is $\tau$. $\tau$ is the time until $u_c$ reaches $2/3$ of $u_e$. It can be computed using $\tau = R \cdot C$. The position of $\tau$ is marked as vertical dashed lines in Figure 2.4 on the right. The greater the capacitance (with constant resistance), the greater is $\tau$. A consequence of this condition is that $\tau$ becomes smaller the greater the distance between the two plates.

The simulation with varying distance $d$ was chosen because different distances between electrodes will have the main influence on the measurement with capacitive proximity sensing. In this thesis, the sensing system provides one electrode of the capacitor. The other electrode is formed by the human body, which is located near the sensing electrode. A model of this setup is shown in Figure 2.5. The figure is derived from Smith's lumped circuit model from his publication *Electric Field Sensing* [SG99]. Although there are other measurement configurations that include two measurement electrodes, the focus will be on this model since this is the only configuration used in this thesis. It is referred to as the loading mode measurement [SG99]. Further sensing configurations are described by Smith [SG99] and Puppendahl [GP15]. The single plate of the capacitor, which is the sensing electrode, is shown in Figure 2.5 as a blue plate. On the one hand, the sensing electrode has a capacitance $C_2$. This capacitance arises between the environment and the sensing electrode. On the other hand, each object (symbolized by the cloud in Figure 2.5) is also part of the environment. The specific capacitance formed between the measuring electrode and the object to be distinguished from the environment is extracted to the capacitance $C_1$. The capacitance $C_3$ is formed between the object and the mass of the environment. The parallel elements $R_i$ and $C_i$ represent the internal states of the object. In the case of, for example, hand recognition, these elements represent the circuit from the hand through the body to the feet.

In this example, the medium between the object and the sensing electrode is air. There could, however, also be another material between the sensing electrode and the object. Two examples of the material placed around the sensing electrode are shown in Figure 2.6. Conductive material placed around the electrode is shown on the left of Figure 2.6. For example, this could be metal. Non-conductive material placed around the electrode is shown on the right of Figure 2.6. This can be, for example, a wooden table. The electric flux lines do not have to represent the real property of the electric flux. They should symbolize that, similar to a Faraday cage, the electric flux does not percolate through the conducting material. In this case, changes in the position of the object cannot be measured. Nonetheless, the electric flux can percolate the non-conductive material as shown

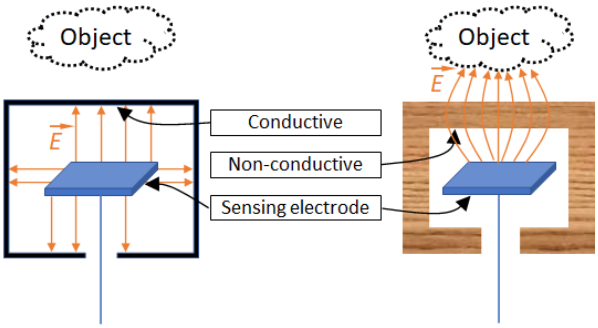



Figure 2.6.: Different material between object and sensing electrode

Figure 2.7.: Rus et al. material selection for seat cushion: conductive fabric and two times conductive thread [RBKK19]

on the right of Figure 2.6. Position changes of the object can still be measured in this case. Capacitive proximity sensors can therefore sense through non-conductive materials and detect changes in the object's position behind non-conductive materials. The capacitance which depends on the distance between the object and the sensing electrode is only one part of the measured capacitance. There are additional conditions that influence the measured capacitance. Following Cular [Cul14], the difference of the relative permittivity of air at 0% humidity compared to 100% humidity is less than 0.001‰. The change in capacitance caused by varying humidity can then be neglected. Changes in the ambient temperature can nevertheless influence the geometry of the sensing electrode. Temperature changes therefore influence the measured capacitance. An empirical estimation of this effect is presented in Section 3.1.9. As shown in Figure 2.6, conductive material between the sensing electrode and the object can also decrease the object's contribution to the capacitance measurement. Water is a conductive material. Even though humidity seems to have little effect on the measurement, a water-covered sensing electrode can no longer sense through the water. In addition to effects that impede the measurement of object distances, the current setup only provides a measurement that encompasses the absolute distance of an object regardless of direction. Nevertheless, a directional measurement is required in many use cases. Puppendahl [GP15] presents the advantages of a driven shield. The driven shielding is attached to the sensing electrode opposite the object. The driven shielding has the same potential as the sensing electrode. As a result, only changes on the side without shielding can be measured significantly.

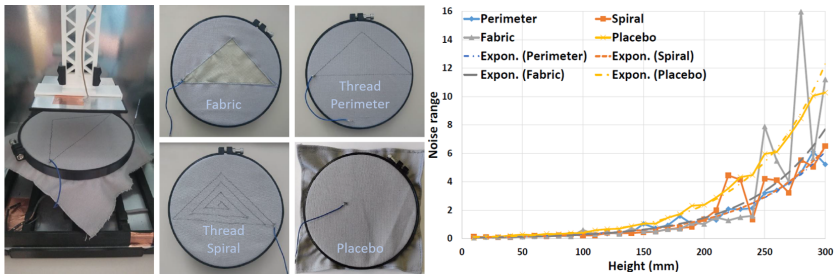



Figure 2.8.: Rus et al. material behavior measurement setup and results [RBKK19]

### 2.1.3. Materials for sensing electrodes

The basic principles of capacitive proximity sensing are explained in Section 2.1.2. Selected material for sensing electrodes remained unmentioned. The material used has an influence on the sensing characteristics. All applications in this thesis rely on copper as the material for the sensing electrodes. On the one hand, unprocessed printed circuit boards are used. On the other hand, self-adhesive copper tape is used to allow flexible application. However, there are various materials that can be taken as sensing electrodes. A literature review of the materials used is presented now. The materials considered are copper, mainly unprocessed printed circuit boards, conductive filament, conductive fabric and two transparent materials: indium tin oxide coated polymers and PEDOT:PSS.

In terms of flexible electrode material, a seat cushion equipped with conductive fabric as sensing electrodes was developed by Rus et al. [RBKK19]. With the help of this enhanced seat cushion, they are able to assess the proximity and movement of the subject on the cushion. Through these measures, they intend to limit the risks of back pain for office workers. They conducted a study with 20 participants to test the performance of their system. Each participant was asked to take different postures on the seat. They then identified the postures using a support vector machine model. During their project, they also analyzed the behavior of the material. The experiments were conducted with different materials and geometries of the sensing electrodes. The experimental setup is shown on the left in Figure 2.8. Rus et al. were able to acquire data from the capacitive proximity sensing setup at different distances from the sensing electrode using the instrument shown at left in Figure 2.8. The noise range of the measurement is shown on the right of Figure 2.8. The conductive filament-based electrodes performed best compared to conductive fabric and the placebo (just a wire). Rus et al. used their sensing electrode materials in an office setup with an office chair. Although this is not an automotive application, many elements of the vehicle interior, such as the seats, are covered with fabric and consist of cushions of varying thickness. Therefore, it would likely be possible to incorporate conductive threads or fabrics into capacitive proximity sensor arrays for automobiles. Rus et al. investigated other sensing electrode materials as well. In another paper, they performed a similar experiment with a copper electrode (unprocessed circuit board), conductive paint, and conductive fabric [RSBK15]. In this publication, they conclude that all of the materials presented would be equally well suited for applications requiring flexible sensing electrodes. If flexible material in the form of conductive thread or fabric is still not suitable because one not only wants to embed the material in existing structures, but also wants the structure itself to become the capacitive sensor electrode, Schmitz et al. [SKB*15] have developed an approach to create 3D-printed objects with embedded sensor electrodes. In this case, the sensor electrodes are formed from ABS material with 5-8% carbon. This material enables them to print 3D objects that can be placed on capacitive touch surfaces, for example. Subsequent touching of different areas of the object can thus be measured.

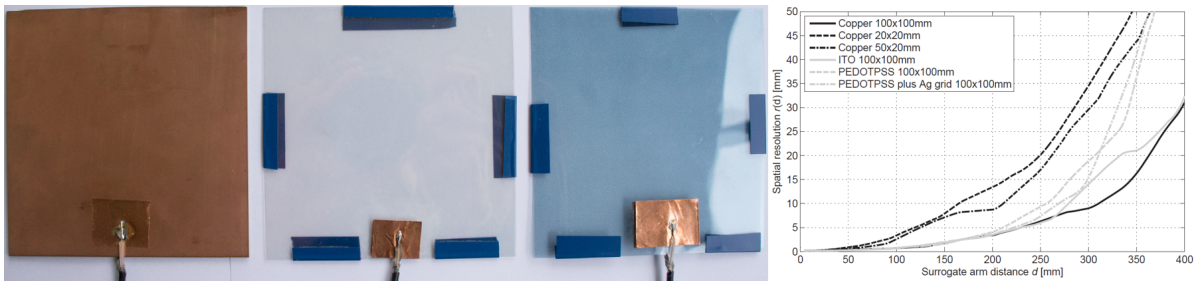



Figure 2.9.: Puppendahl electrode materials (copper, ITO and PEDOT:PSS) [GP15]

Rus et al. used the same capacitive proximity sensing toolkit that is used in all projects in this thesis. It is the capacitive proximity sensing toolkit as presented by Puppendahl et al. [GPBB*13]. Fortunately, Puppendahl [GP15] has provided measurements on characteristics of these capacitive proximity sensors that examine the dependencies on the sensing electrode material used. In the investigation by Puppendahl et al. additional material for sensing electrodes is examined. Indium tin oxide (ITO) coated transparent polymers and PEDOT:PSS [CJC*06] are used in particular. An example of these sensing electrodes and a copper electrode is shown in Figure 2.9. Using these electrodes and the sensing toolkit, Puppendahl conducted an experiment with a conductive tube as a surrogate arm. The distance between the tube and the sensing electrodes is adjustable. The sensor outputs are measured at different electrode distances from the pipe. The measured resolution of the sensing electrodes at different distances is shown on the right in Figure 2.9. The measuring electrode geometry is also noted in the legend of the diagram. The copper electrode shows the best spatial resolution. Based on these measurements, copper is chosen as the basis for the sensing electrodes of this thesis. The overview of different output resolutions depending on the distance to the sensing object is still necessary to estimate essential applications for capacitive proximity sensing in vehicles. Based on the relationship between distance and resolution shown in Figure 2.9, suitable vehicle structures can be selected for research questions RQ1 and RQ2 based on the resolution required for the application and the distance between the object to be monitored and the vehicle structure to be used. Transparent application of the sensing electrodes can also be indicated if the sensing electrodes cannot be mounted behind the selected vehicle structure and the setup is still to be unobtrusive.

### 2.1.4. Applications

Numerous applications have been developed based on the physical properties presented in Section 2.1.2. Practical research on these applications is now presented. The focus is on human machine interfaces and interactions based on capacitive proximity sensing. Even though the closest relation is to automotive research, applications with capacitive proximity sensing, outside the automotive domain, are presented in Section 2.1.4.1. These applications are related due to the nature of interaction and interfaces. Vehicle applications based on capacitive proximity sensing are then presented in Section 2.1.4.2. These applications already provide opportunities for human machine interaction and types of automotive human machine interfaces. In the concept presented in Chapter 3 the awareness of related applications is required to develop significant capacitive proximity sensing-based applications in vehicles to answer research questions RQ1 and RQ2.

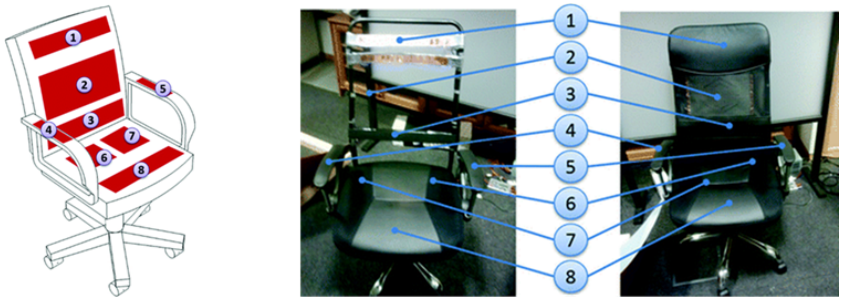



Figure 2.10.: The capacitive chair [BFW15]

#### 2.1.4.1. Non-vehicular

Research into capacitive proximity sensing is also taking place outside the automotive domain. The results of this research can have an impact on the development of in-vehicle systems. Capacitive proximity sensing is already being investigated in research in areas such as ambient intelligence. An application example related to this thesis is now presented. The analysis of driver states using an instrumented driver seat is part of this thesis. An office chair equipped with capacitive proximity sensors is therefore selected as the first non-vehicle related work. Braun et al. [BFW15] used an ordinary office chair and equipped it with capacitive proximity sensing. The concept and the mounting of the sensing electrodes are shown in Figure 2.10. The sensing electrodes are numbered from one to eight. With this system, Braun et al. try to relieve office workers. Since office workers spend a lot of time sitting in a chair, changing their sitting posture frequently could reduce the risk of health problems such as back pain. To this end, a data processing algorithm is being designed that is capable of recognizing five different sitting postures. It can additionally detect the occupancy of the seat. At its core, a support vector machine model is applied to distinguish postures and occupancy. Using this setup in a user study with ten subjects, an average accuracy of 98.5% correctly classified postures is achieved. The detection of postures in combination with the duration of the posture can be used to inform the user that the position on the seat should be changed. In addition, the system by Braun et al. can be used to measure other physiological states. Using a frequency analysis method, they are able to detect the user's breathing rate. They are also able to derive a relative activity level. Based on the detected activity level, the activity of the worker on the office chair can be quantified. Based on this quantification, they distinguished three classes of activity: not at the chair, active work (writing, typing), and inactive work (e.g., reading). This publication does not directly address the research questions of this thesis. Nonetheless, this publication demonstrates the ability of capacitive proximity sensing to monitor user state such as breathing rate, posture, and activity. However, while office workers should change their position frequently, it is difficult for drivers to change their position in the driver's seat in a similar way to an office chair. Position detection can nevertheless be used in out-of-position detection scenarios, for example, to prevent the driver from overlapping with airbag deployment zones. Since the driver is statically pressed against the backrest, this publication is also an indication that breathing rate could be detected in an automotive scenario.

Another application will be part of this thesis: the mood preservation of children in a child seat. Since this may involve emotions, another furniture application is selected from related work: Rus et al.'s "Emotive Couch". Rus et al. [RJBK18] recognized that the most common method of measuring emotions is by observing the face. They state that this can lead to privacy concerns. They decided to choose motion-based indicators of emotion so that no facial images need to be captured. To capture these movements, an ordinary couch is equipped with eight capacitive proximity sensors. The sensors are integrated into the upholstery of the couch. In this way, they

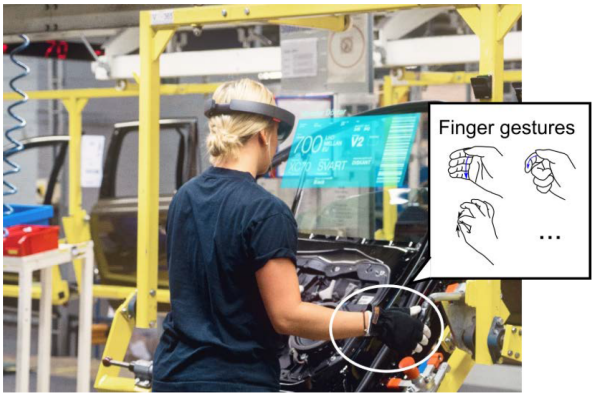



Figure 2.11.: Nguyen et al. application concept: Supporting workers with head mounted devices at the assembly line [NRL*19]

are able to distinguish between five different body postures of the user. These postures form a basis for emotion recognition. Another indication is the movement of the subject, which can also be detected. Using this setup, Rus et al. conducted an experiment with 15 participants. Each participant watches videos related to the emotions to be recognized: anxiousness, relaxation, interest, sadness, and joy. This initial set of emotions is then reduced to: relaxation, interest, and anxiety. The set is reduced due to incorrect classifications for the sadness and joy classes. With this set and 15 participants, they achieved a remarkable emotion recognition accuracy of 77.7%. Apart from the technical features of Rus et al.'s work, they already point out that capacitive proximity sensors maintain privacy compared to cameras. Nevertheless, they do not prove or reference this statement. In this thesis, this statement is examined to address the research question RQ3.

These two related publications focus on physiological conditions of users and therefore do not necessarily require interaction. Nevertheless, human computer interaction is also considered in research question RQ2. Another research paper that uses capacitive proximity sensing in non-automotive applications for human computer interaction is now presented. A capacitive proximity sensing-based device for gesture recognition is presented by Nguyen et al. [NRL*19]. Sensing electrodes are integrated into a worker's glove. The device can be used to enable interaction between workers and their head-mounted device using finger gestures, as shown in Figure 2.11. Fourteen different finger gestures can be distinguished. With this setup, they conducted an experiment with ten subjects. Each subject performed the gesture set 25 times. With this data, they evaluated three classifiers with ten-fold cross-validation. The best F1 score is reached with an LSTM [HS97] neural network. In particular, the F1 score of the LSTM classifier is 0.975, so they show impressive accuracy. This application was chosen because automotive gesture recognition applications are also presented and developed in this thesis. The applications presented in this thesis will not rely on additional devices. They will simply rely on the existing vehicle structures. Additionally, this research is particularly interesting to this thesis because it demonstrates the integration of capacitive proximity sensing into an augmented reality or virtual reality environment. This is particularly relevant to this thesis, because an application for augmented head-up displays using capacitive proximity sensors will be presented.

Another gesture recognition system based on capacitive proximity sensors is selected. This is picked because capacitive proximity sensors are often arranged in an array structure. Based on this structure, the movements of objects over this structure can be estimated. A system consisting of an array structure of capacitive proximity

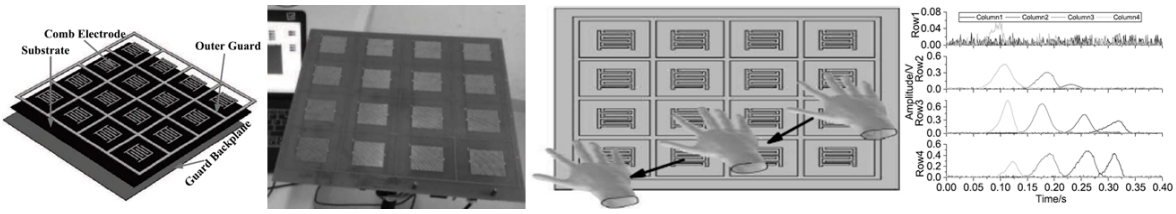



Figure 2.12.: Ye et al. array concept with exemplary hand movement and corresponding sensor amplitudes [YHLQ18]

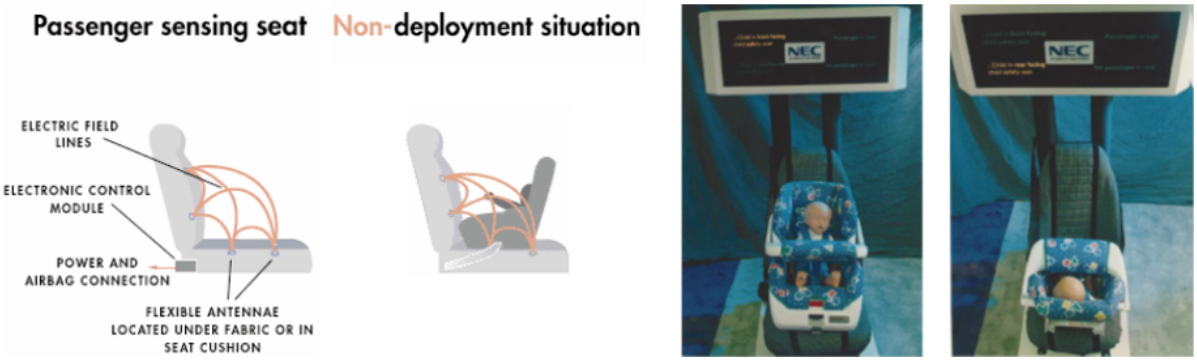



Figure 2.13.: Child seat detection system of Smith [SG99] and NEC [JOOS01]

sensors is presented by Ye et al. [YHLQ18]. Due to their design, they are able to detect hand movements. They state that the developed system is capable of measuring hand movements at a distance up to 45 cm. The concept, the prototype and an exemplary hand movement measurement are shown in Figure 2.12. Each comb electrode is guarded against another one. The course of the output of the capacitive proximity sensor is illustrated in the chart in Figure 2.12. Depending on the hand position, the highest amplitudes of the sensing electrode output are shown when the hand hovers over it. The smallest amplitudes are shown in row one, because the hand is not hovering over it during the motion shown. This study was chosen to show that planar arrays can have advantages in position sensing of hovering objects. That said, there are few planar surfaces in existing vehicle structures that would provide the capability to build such a large sensor array. Therefore, the systems in this thesis do not rely exclusively on array structures. Nonetheless, there are systems in this thesis that incorporate small planar arrays of sensing electrodes.

#### 2.1.4.2. Vehicular

Some applications of capacitive proximity sensing outside the automotive field were shown in Section 2.1.4.1. They were studied because their operation can be applied or adapted to the automotive domain, as they have significant applications that could help drivers and passengers in vehicles. We now move from non-automotive applications to the automotive domain as these are most closely related to this thesis. One challenge in vehicles mentioned in Chapter 1 is the safe transportation of children. In view of this challenge, child seats are used as a passive safety device to mitigate the consequences of an accident. Although the challenges presented in

Chapter 1 focus on the consequences for children left in vehicles or unattended, research faces another problem related to child safety seats. In particular, the position of child seats in vehicles is examined. Rear-facing child seats, especially on the front passenger seat, can overlap with the deployment range of the front passenger airbag. Back in 1999, Smith [SG99, pp. 101 – 105] collaborated with NEC [JOOS01] to develop a capacitive proximity sensing-based system to distinguish rear-facing and forward-facing child seats. The resulting concept with electrode position is shown on the left in Figure 2.13. Four measuring electrodes running in shunt mode are used to perform sixteen measurements. The concept was implemented in an application as shown on the right in Figure 2.13. Smith also points to real-world problems that occurred during a presentation of the system. While he states that the system works, in one particular case the adhesives on the electrodes came loose. This changed the geometry of the application and prevented the model from working. Smith reattached the electrodes and the presentation continued to run successfully. This demonstrates the requirement for a structure that is rigid or at least observable in its changes. In contrast to the approach in this thesis, Smith's application relates to occupancy or presence detection integrated into the vehicle's seating structure. In this thesis, sensing electrodes are only installed in the child seat. Since the sensing electrodes are integrated into the child seat, the system can be used autonomously in different vehicles without the need for additional vehicle structures. Capacitive proximity sensing will also be applied to physiological characteristics such as the heart rate or sleep state of the child in the child seat. Nevertheless, research question RQ1 is addressed by the application. There are other capacitive proximity sensors that address child safety in vehicles. While Smith uses capacitive proximity sensing to detect the orientation of a child seat, research by Ranjan et al. [RG13] is moving toward a system that is integrated only into the child seat. With this system, they are trying to overcome the problems that arise when a child is left in the vehicle. To prevent possible heat stroke, their system detects if a child is still in the vehicle while the driver has left the car. If so, they use a GSM device to notify the driver that the child is still in the car. The focus is on a reliable alerting system that calls the driver if there is no response, calls the parents, and then dials emergency if there is still no response. Similar to Smith's system, this is a presence detection system. In this thesis, other functions based on an utilized child seat will be provided.

To extend the awareness of applications of capacitive proximity sensing in vehicles, another application is picked out. As stated in Chapter 1, evidence for research questions RQ1 and RQ2 will also be provided by applications in the field of authentication. In 2016, Braun et al. [BWF16] patented a system which includes capacitive proximity sensing for identification, which could be used for authentication. The sensing electrodes are positioned inside the driver's seat. If a person occupies the seat, the person's pose is detected. Pre-recorded data is used to identify the driver. The prerecorded data consists of data from known drivers. The positions and the measured output of the capacitive proximity sensors with respect to the positions are stored. Subsequently, individuals can now be identified based on the output of a machine learning model trained on this data. The mechanism is related to the biometrics of the person. As already mentioned in Chapter 1, authentication devices that are based on biometric data rely on data that cannot be changed. In this thesis, it is shown that capacitive proximity sensing can be used for changeable authentication applications. Nevertheless, the patent of Braun et al. is based only on existing vehicle structures and relies on capacitive proximity sensing. It therefore contributes directly to research questions RQ1 and RQ2. The interaction required for RQ2 is also considered in the training phase of the system. After that, the running authentication system does not require any interaction from the driver. During the ongoing authentication, the system is a human machine interface on the vehicle side without interaction and therefore RQ1 is more likely to be addressed here.

The applications shown so far focus on interfaces without interaction. Interaction in vehicles can also be realized by using capacitive proximity sensing. In another publication by Braun et al. [BNS*14] an interactive vehicle armrest is developed which is shown in Figure 2.14. With the armrest, the user can perform various finger and multi-finger gestures, as shown on the right in Figure 2.14. Free-air and touch-based gestures can be distinguished by the system. The system was tested with eleven participants and the evaluation measured


Figure 2.14.: The active armrest, prototype and gesture set [BNS*14]

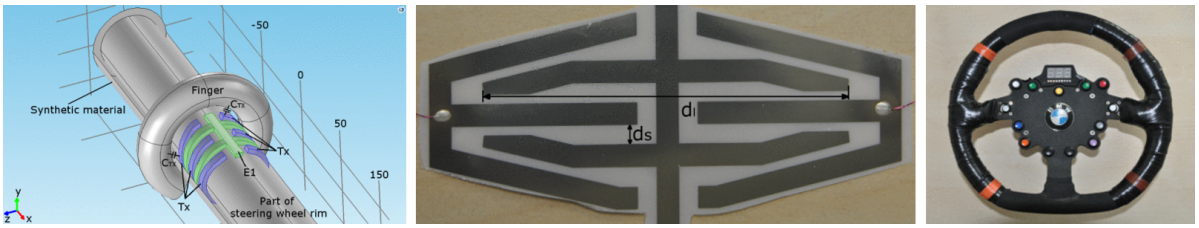



Figure 2.15.: Mühlbacher et al. steering wheel sensing setup [MKMF*17]

a recognition rate of 77.3% to 90.9% for touch-based gestures and 45.5% to 81.8% for free-air gestures. The performance was acceptable to the researchers and they conducted an additional test scenario with the participants. In this scenario, the active armrest was used as a control device for a music player. The subjects were then asked about their preferences. Most people preferred the touch-based gestures. Since the device is invisibly integrated into a vehicle structure and it is based only on capacitive proximity sensing, research questions RQ1 and RQ2 are addressed. The provided gestures are mainly symbolic hand gestures. In this thesis, it is shown that capacitive proximity sensing in an automotive environment is capable of providing more complex and precise control compared to symbolic gestures that do not rely solely on the driver's hands.

In this thesis, there are also systems that rely on hand-based gestures. In particular, a hand motion detection device will be presented in Sections 5.1 and 5.2. Both systems rely on sensors integrated into the steering wheel as the only vehicle structure used. This vehicle structure as the basis for capacitive proximity sensing is also being investigated by Mühlbacher et al. [MKMF*17]. In their system, capacitive proximity sensors are mounted on the steering wheel. A model of the application with finger, the sensing electrode geometry used and the steering wheel equipped with the sensors is shown in Figure 2.15. Mühlbacher et al. try to recognize the stress level of the driver. The goal of their work is not only to detect the stress level by using capacitive proximity sensing. Rather, capacitive proximity sensors are added to the steering wheel to augment a number of sensors. Capacitive proximity sensors are to be used to incorporate the position and movement of the hand into a feature vector for a cellular neural network. In addition, data from an electrodermal activity sensor will be included. This system is used to measure skin resistance. Increased sweating thus influences this sensor. In addition to an electrodermal activity sensor, an electrocardiogram sensor is included to measure heart activity. An electroencephalogram sensor is also included. 22 participants were outfitted with these sensors in a study. Each participant underwent two scenarios. Scenario one involves a five-minute unrestricted drive in a driving simulator. In scenario two, participants drive the same route but must maintain a speed between 60 and 100 km/h. During the scenarios, questions must be answered by the participants. This is intended to increase the stress level of the driver. The


Figure 2.16.: Camera-based driver monitoring system [MSS20]

collected data is used to train a cellular neural network and other competing classification models. By using all available sensors, the accuracy is 92%. The cellular neural network shows the best performance compared to classifiers such as support vector machine, naïve Bayes, random forest, and a simple multilayer perceptron. By excluding capacitive proximity sensing, the best trained classifier achieves 82% accuracy. Thus, the accuracy of the system is increased by 10% by using capacitive proximity sensing.

## 2.2. Competing procedures for vehicular human machine interfaces

Applications for capacitive proximity sensing in vehicles were shown in Section 2.1.4. There are many other sensor systems that could or already can enable similar capabilities to capacitive proximity sensors. In addition, these sensors may have advantages that capacitive proximity sensors cannot match. Capacitive proximity sensors also have advantages that need to be named so that a suitable sensor system can be selected for applications in vehicles. Since research questions RQ1 and RQ2 focus on human machine interfaces and interaction in vehicles, some applications and research in these areas without capacitive proximity sensors will now be shown. We now also discuss some features of these systems. The selected features are gesture control, physiology monitoring, and authentication. We begin with imaging techniques. Imaging is considered important for human computer interaction in cars because it is widely used. Cameras and their physical principle as well as the collected data have many differences from capacitive proximity sensing. Research question RQ3 is not addressed here. Privacy concerns are addressed in Section 2.4.

In developing applications based on capacitive proximity sensing, I often encountered image processing as a competing sensor system that can enable similar functions. One application that is often based on cameras is driver monitoring [Bay18, DS 19, MB14, SBM*16]. Cameras are installed in center consoles or in the steering wheel hub, for example. In most cases, the camera is pointed at the driver's upper body, including his or her face, to capture images of the driver's upper body and face. To show an example of such a human machine interface in vehicles, I have selected a recent research paper by Murugan et al. [MSS20]. The reason why this technology is considered competitive is shown in Chapter 5, where similar functions are enabled only with capacitive proximity sensing. Murugan et al. place an infrared camera in front of the driver to capture the driver's face. Using an optical flow algorithm (Kanade Lucas Tomasi), they are able to distinguish between five different driver states. The states are shown in Figure 2.16. They tested their algorithm with ten test subjects in a driving simulator. Each subject had to drive a distance of one mile. They took measurements at different times, from 0 a.m. to 4 a.m.. The level of difficulty was increased by distracting the subjects while they drove. For example, subjects had to write text messages, answer questions and take phone calls. The subjects then had to drive for another 80 minutes until they could no longer hold back their fatigue. The collected data is then used to train and test the processing models. The highest average accuracy of 64.1% is achieved by an ensemble classifier that is not further specified. As shown in Figure 2.16, the camera must be in line of sight of the driver. In Chapter 5, we will


Figure 2.17.: Gesture recognition based on image processing as provided by Ohn-Bar et al. [OBTT12]

see that capacitive proximity sensing is capable of detecting similar physiological states without line of sight. Monitoring the driver's face through a camera can raise privacy concerns. This addresses research question RQ3. For more details on privacy concerns raised by devices in human machine interfaces in vehicles, see Section 2.4 and Chapter 6.

In addition to physiological measurements, image processing is also used in gesture recognition devices. Actual systems that are included in serial vehicles are presented in Section 6.1, because they are analyzed concerning privacy issues that could emerge due to the application of cameras. A system that is not included in Section 6.1 is picked here. Ohn-Bar et al. [OBTT12] mounted a depth camera that is also capable to retrieve color information into the vehicle roof. The camera is pointing towards the center console of the vehicle as shown in Figure 2.17. Due to this setup, color and depth can be retrieved. Only a region of interest that is marked in Figure 2.17 is analyzed. This setup allows six different symbolic gestures to be distinguished, and the system can distinguish the actual user of the system. In particular, the system recognizes whether the driver or passenger is using gestures. To test the system, eight participants used the system under real conditions. In other words, the test subjects drove a vehicle themselves. Due to the test under real conditions, changing light conditions are also included in the experiment. Although changing lighting conditions affect the image processing algorithms, an impressive mean accuracy of about 95% was achieved in a five-fold cross-validation on a dataset of 613 gestures from eight subjects. Similar to the physiological condition monitoring system, the camera must be integrated so that there is a line of sight. The camera must therefore be integrated into the interior design so that it appears obtrusive and, as shown in Figure 2.17, more information than required is captured by the camera system.

Since cameras are not the only option for monitoring gestures in vehicles, other detection systems are selected. One system is based on an array of infrared sensors. Tateno et al. [TZM19] applied such a sensing technique in the automotive domain. Using a series of infrared sensors, Tateno et al. are able to derive hand gestures so that, for example, vehicle infotainment can be controlled by the driver. Similar to most gesture recognition devices, they do this to address problems of inattention based on manipulation of automotive controls. Due to the data of the infrared sensors and processing using a convolutional neural network model [LBBH98], Tateno et al. are able to recognize six different static gestures and four different dynamic gestures. They tested their system under laboratory and real-life conditions. Under these conditions, 100 samples of dynamic gestures are collected. The average accuracy in this case is about 97%. For static gestures, 3,500 samples were collected from five subjects. In this case, a mean accuracy of about 87.5% is achieved. While these numbers refer to laboratory conditions, they also conducted the experiment in a car. During their experiments, they collected 700 static gesture samples. Under these conditions, they measured a mean accuracy of 87.7%. The comparison between the results in the lab and in the car shows that the system seems to generalize well. They also recognized that the system works better when the environment is completely dark. They conclude that the system is affected by lighting conditions. This

is a disadvantage compared to capacitive proximity sensors. These sensors are not influenced by changing light conditions.

Various sensor systems have been presented so far in this section. Applications based on cameras or infrared sensors have been presented in particular. There are further applications of sensors in vehicles that can compete with capacitive proximity sensing. There are pressure sensors that can be installed under cushions or flexible material, as shown by Lorenz [Lor11]. If these can be placed under flexible material, similar to capacitive proximity sensing, a large impact on interior design is not expected. Contact is required, so movement in the air cannot be detected by these sensors. Other competing technologies, or in other words, the related works in terms of the specific features of the designed applications presented in this thesis, are shown where the applications of this thesis are presented. The analysis of other sensor systems that can enable similar properties is part of the concept of this thesis, shown in Chapter 3. It is mandatory to assess those systems to rate the significance of the application of capacitive proximity sensors in the specific case. The term competing might furthermore be misleading. Of course, the application of specific sensor systems is not mutually exclusive. In particular the fusion of capacitive proximity sensors and other sensors to form a multimodal user interface as for example provided by Manawadu et al. [MKI*17] can improve the overall robustness and acceptance of human machine interfaces.

## 2.3. Benchmarking

Several sensor systems already in use in applications enabled by capacitive proximity sensing were presented in Section 2.2. It is therefore of interest which sensor system is considered best suited for the respective measurement, if a sensor fusion is not intended. To assess if the use of capacitive proximity sensors is more appropriate than the use of other sensors for an application, a benchmarking procedure is included. This procedure is based on the benchmarking process of Braun [Bra14, pp. 47–61]. Braun identifies metrics for evaluating combinations of sensors and applications. With respect to sensors, three groups of sensor properties have been identified: sensor performance characteristics, pervasive metrics, and environmental influences. The three most relevant characteristics for each group are marked with an asterisk in the following list extracted by Braun.

- Sensor performance characteristics
  - Resolution*
  - Sample rate*
  - Power consumption
  - Detection range*
- Pervasive metrics
  - Unobtrusiveness*
  - Required bandwidth (in sensor networks)
  - Processing complexity*
  - Robustness (physical and quality of service)*
  - Interoperability
- Environmental influence
  - Disturbance Frequency*
  - Calibration Complexity*
  - Unique limitations*

| Feature | – | - | o | + | ++ |
|---|---|---|---|---|---|
| Resolution | very coarse | coarse | normal | fine | very fine |
| Update Rate | less than once per second | slower real-time | real-time | faster real-time times per second | more than 100 |
| Detection Range | touch | less than one meter | less than 5 meters | less than 20 meters | more than 20 meters |
| Unobtrusiveness | open large system | open small system | hidden system, large exposure | hidden system, small exposure | invisible |
| Processing Complexity | single sensor CPU | 10+ sensors CPU | single sensor embedded chip | 10+ sensors single embedded chip | no further processing |
| Robustness | single point of failure | error detection | quality of service | self-recovery | fully redundant |
| Disturbance Frequency | very frequent | frequent | average | unlikely | highly unlikely |
| Calibration Complexity | very hard | hard | normal | easy | very easy |
| Unique Limitations | very critical | critical | average | not critical | none |

Table 2.1.: Feature matrix denoting capabilities required for a certain rating [Bra14, pp. 47–61]

Each of these characteristics is referred to as a feature in the following. Braun applies a five-level ordinal scale to each feature. For further clarification of the individual features, a feature matrix with the three most important features is shown in Table 2.1. While Braun does not include power consumption among the top three sensor performance features, it can be argued that this feature may become more important in mobile applications. Scales used to calculate a benchmarking score are shown in Table 2.1. This score is the result of a benchmarking process, which is shown in Figure 2.18. Before the score can be computed, an application must be defined. The application is considered as a combination between the subject emissions to be measured and a sensor system that can measure these emissions. Then the feature matrix is detailed as shown in Table 2.1. Weights for the application against these features are determined. Selections from the now detailed feature matrix are translated into a numerical scale from 0.0 for the leftmost position to 1.0 for the rightmost position with a step size of 0.25. The result of this operation forms the actual feature matrix. In addition to the sensors, there is also an evaluation for the application. With the help of the evaluation, weights are assigned to the individual features. A weight vector is then generated. The final benchmark score is calculated using the feature matrix and the vector of weights.

Since the computation of the benchmark is needed for this thesis in Chapter 3, the required equations will now be explained. For further clarification, the equations are provided with an example as considered by Braun: indoor localization in a public shopping area. He specifies a required localization accuracy of 0.5 m. In addition, a large area is to be covered. In summary, the weights for the application are composed as in the following vector:

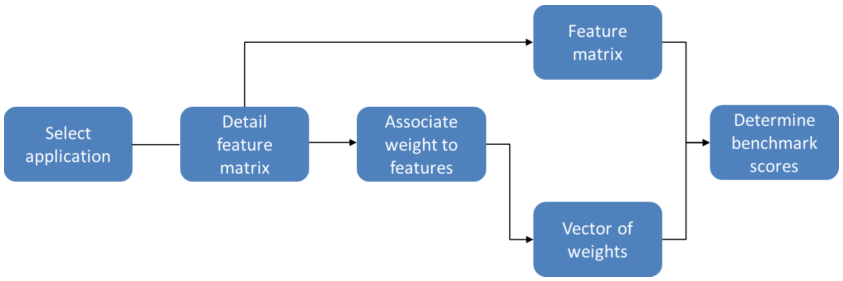



Figure 2.18.: Benchmarking process following Braun [Bra14, pp. 47–61]

(o + ++ - -- + o - o)$^T$; or translated to numeric values: $\vec{w} = (0.50\ 0.75\ 1.00\ 0.25\ 0.00\ 0.75\ 0.50\ 0.25\ 0.50)^T$. In this application, the detection range seems to be very important, while the processing complexity is unimportant. $\vec{w}$ is static for all sensor systems that could enable this application. A feature vector for the sensor system is required. In Braun's example, high-resolution cameras are chosen as the sensor system for the application. The feature vector is formed as (++ + ++ - -- o + - ++)$^T$; or translated to numeric values: $\vec{r} = (1.00\ .75\ .00\ .25\ .00\ 0.50\ 0.75\ 0.25\ 1.00)^T$. Based on the feature vector values, the sensor system shows good performance in resolution, detection range, and unique limitations. The worst performance is for processing complexity. These two vectors are inputs to Equation 2.4. The scalar benchmarking score is denoted as $b$ in Equation 2.4.

$$b = \frac{\vec{r}^T \cdot \vec{w}}{\sum \vec{w}} \tag{2.4}$$

Equation 2.4 can be used to calculate the benchmark score for the indoor localization example. A score of $b \approx 0.76$ is obtained. Braun extends the equation to form a normalized benchmarking score. As shown in Equation 2.5, the feature vector is adjusted for the sensor system, where $o$ denotes the number of features. Replacing $\vec{r}$ with $\vec{r}_{norm}$ yields the normalized benchmarking score of $b_{norm} \approx 0.63$.

$$\vec{r}_{norm} = \frac{\vec{r} \cdot o \cdot 0.5}{\sum_{p=1}^{o} \vec{r}} \tag{2.5}$$

With this model, sensors can be tested to see if they are the best fit for a system. The development of significant application for vehicles is important to find clues for research questions RQ1 and RQ2. Therefore, Braun's approach is reused to form part of the concept presented in Chapter 3.

## 2.4. Privacy concerns regarding vehicular human machine interfaces

So far, mainly technical aspects of the human machine interface in vehicles and capacitive proximity sensing have been presented. There are, however, other aspects that must be considered when evaluating sensor systems for human machine interfaces in vehicles. One of these properties is unobtrusiveness. Unobtrusiveness is related to privacy preservation. Privacy-preserving systems not only contribute to unobtrusiveness, but are also a legal matter, since the European Union has adopted the General Data Protection Regulation [Cou16]. Related work that addresses the analysis and root causes of in-vehicle and off-vehicle privacy issues is presented in Section

2.4.1. The analysis and causes of privacy concerns lead to research on how to address these concerns. This is presented in Section 2.4.2.

### 2.4.1. Analysis and causes of privacy concerns

We begin our examination of related work, on the topic of privacy, with a non-automotive example. In this example, we examine users' privacy concerns in social networks. The impact of privacy concerns on social network formation is explored by Gaudeul et al. [GG17]. The investigation is based on a study with 125 subjects. The subjects are evenly distributed among five groups. A social networking game with two phases is designed as an experiment. In phase one, personal information is collected. In phase two, participants can choose a level for disclosing personal information. They can then select other individuals to form a network. In Gaudeul et al.'s study, a connection is established when both participants have selected each other. They can also choose to pay a fee for the service. The aim of the study is to find out how the possibility of different data disclosure options affects the formation of individual networks. Several hypotheses are tested. One is that preference for social consent should increase willingness to disclose information in hypothesis one. A metric for privacy concerns is presented: Privacy Cost (PC). It is shown that disclosure of real name and information causes higher PC than disclosure of name only. Gaudeul et al. show that PC for disclosing only the real name is greater than PC for false names. A high PC should lower the willingness to disclose information in phase two. This is covered by hypothesis two. These hypotheses are intended to contribute to the main hypothesis of the paper: the absence of past interactions of an individual influences the choice of disclosure of information by another individual. Five outcomes are captured by the analysis of the study. Subjects contribute less to the network when privacy concerns arise due to disclosure of name and subject information. Result three is of particular interest. It concludes that PC is more important to individuals than social recognition. This publication was selected to show the value of privacy-preserving behavior of the system. It is therefore of interest to the analysis of the car user's decision regarding capacitive proximity sensing and privacy in Section 6.2.

The previous analysis by Gaudeul et al. focuses on a non-automotive application. Nevertheless, research is also being conducted in the automotive sector. Even if legislation mandates privacy by design to ensure that the technology used incorporates the highest level of data protection [Cou16], vehicle users may not have any privacy concerns even though there are systems installed in their vehicle that may be mining sensitive information. This issue is investigated by Bloom et al. [BTRB17]. Bloom et al. present work on people's privacy concerns in connected autonomous vehicles. They conducted a comprehensive study with 302 participants in five cities of similar size in the United States. Some of the cities selected have autonomous vehicles operated by the transportation network company Uber. In doing so, they aim to increase representativeness. In their survey, they capture people's knowledge about data analysis systems in cars. Participants in their study can choose to limit data collection. In their study, they measure that knowledge about enabled tracking processes varies and privacy concerns create discomfort among participants. Despite this, 57% (172) of participants use Uber/Lyft. Five minutes or more are spent by 54% of participants to enable options that disable data collection. They conclude that scenarios such as tracking and identification cause great discomfort. However, using data to improve navigation does not seem to cause the same discomfort. Bloom et al. also point out that people seem to think they have no choice about data collection. This can occur when the participant thinks that tracking cannot be avoided.

In addition to general questions about user perceptions of privacy in social networks and cars, users may also have specific concerns about a particular capture system. Since cameras are a main component of the investigation in Chapter 6, research on privacy concerns, with reference to cameras, is now presented. Cameras are used in many assistance systems, such as ambient assisted living. The use of these sensors raises questions about data protection. Caine et al. [CaC12] conducted a study with 18 participants. The average age of the participants is 81 years. The participants are divided into three groups. One group is recorded with a stationary


Figure 2.19.: Assessment of privacy enhancing behavior in camera monitored environments [CaC12]

camera, a second group is recorded with a stationary robot and the last group was assisted by a mobile robot. Two of those systems are shown in Figure 2.19. Each robot carries a camera. In their study, they analyze privacy-enhancing behavior toward these systems. When people behave unnaturally to improve their feelings of privacy, this is called privacy-enhancing behavior. An example of privacy-enhancing behavior is shown in Figure 2.19. They found that the camera causes most of the privacy-enhancing behavior.

In addition to snapshots of current sensing systems and the data recorded by these sensors, the evolution of these sensing systems can lead to privacy issues, even if the original system did not collect privacy-sensitive information. This process is also examined in Section 6.1 of this thesis. An overview of vehicle owner privacy concerns arising from evolving technologies is shown by McDonald et al. [MC05]. People's awareness of technologies that cause privacy concerns is explored. First, systems that are not initially used for tracking are presented. As these systems mature, they become interesting for people tracking. For example, the New York MetroCard was introduced as a subway usage system, but then it was used by police to track people. This is made possible by data collection, which is not necessary for the original purpose of the system. McDonald et al. find that although the systems did not have a feature that included privacy concerns when they were designed, privacy-relevant patterns can be captured that can be used later. Six technologies are examined: Black Boxes (event data recorders), traffic cameras, GPS transponders, OnStar, E-ZPass, and Highway Use Tax. Although these systems were not defined to capture privacy-sensitive information, their evaluation has changed to capture sensitive information about driver behavior.

### 2.4.2. How research addresses privacy concerns

Different aspects of assistance systems in the automotive and non-automotive sector were presented in Section 2.4.1. All of these issues affect the privacy of users. Of course, these issues are already the focus of research. How the problems are addressed in related research is now shown. The issue of cameras being able to capture data that affects privacy is explored by Martin et al. [MTT14]. In their paper, they note that cameras are used in driver monitoring systems to capture images of the driver. The captured image of the driver is often unedited. This may contain more information than necessary. For example, a system that detects the driver's gaze in the images could allow the driver to be identified. To address this problem, an image filter is being developed by Martin et al. The filter disables driver identification from the captured image, as shown in Figure 2.20. However, gaze recognition is retained. 20 subjects participated in an evaluation under laboratory conditions. A gaze recognition rate of 71% results when using filtered images, as shown by Martin et al.. They state that this recognition rate

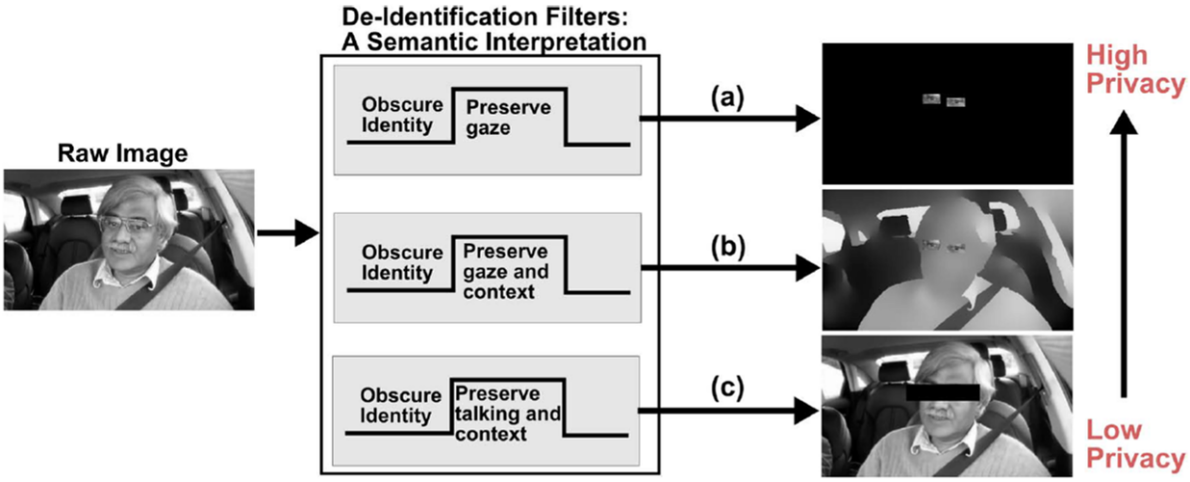



Figure 2.20.: Tackling privacy threats in driver monitoring systems [MTT14]

indicates no significant loss of information due to the image filter. With this approach, the identity of the driver is preserved by the camera with full system functionality.

In addition to avoiding cameras, for example when they are replaced by capacitive proximity sensors, researchers have conducted studies using situation-aware robots with cameras. Fernandes et al. [FYDS16] developed a system which detects privacy sensitive situations. In addition to system development, they conducted an online survey with 449 participants. They measured that people value privacy at home. Participants are also most concerned about cameras that capture nudity. A major concern with cameras, as they are one of the only sensors that can capture an image of a naked person. Comfort with a camera-equipped robot is increased by the robot's ability to look away when a person is naked. The authors do not show a solution when a person needs to be monitored when naked (e.g., fall detection), nor do they say when the system should look back at people. Moreover, for in-vehicle surveillance systems, nudity may not be the main privacy issue for drivers.

## 2.5. Summary

Not everyone is familiar with capacitive proximity sensing. Its ability to measure through non-conductive material even hides its existence. It is therefore necessary to understand the basic properties and become familiar with the sensing system. That is why the background and physical properties of these sensors were presented in Section 2.1. In simple terms, the output of capacitive proximity sensors is related to their environment and the objects in that environment. Changes in the object position affect the electric field and thus the output. It can be compared to changes in the distance between the plates of a plate capacitor. The properties of selected materials are also presented. For example, the selected materials can be transparent. Because of the transparency, the sensing electrodes could be applied to touch screens, for example. Some of the presented materials are flexible or even fabric-like. They were selected because many materials near drivers or passengers in vehicles are based on cushions. Capacitive proximity sensors can be hidden under these cushions. Applications of capacitive proximity sensing were also presented. Even though this is a thesis on automotive applications, some non-automotive applications were shown to demonstrate the capabilities of capacitive proximity sensing and what might be pos-

sible in automobiles. Automotive applications of capacitive proximity sensing were also presented. In this case, these applications address parts of the problems presented in the applications in this thesis. Nevertheless, it is shown that there are still open issues. Additionally, established sensor systems in cars are presented. These sensor systems are based on cameras, infrared sensors or pressure sensors. This is only a selection of possible sensors, since there are, of course, other sensors in the automotive industry. Nevertheless, on the one hand these systems form the basis for the research questions RQ1 and RQ2, whether these systems could be replaced, or on the other hand refer to parts of RQ1 and RQ2, whether these systems could be extended by capacitive proximity sensing. In addition to applications in vehicles, Braun's benchmarking model was also presented. Benchmarking is required to develop a concept to gather evidence for RQ1 and RQ2 based on meaningful applications.

Afterwards, privacy concerns were addressed in Section 2.4 so that research question RQ3 is addressed. Privacy concerns of vehicle users or more general users of assistance systems were presented in Section 2.4. So far, few manufacturers are applying the potential of capacitive proximity sensors discovered in ambient intelligence to the automotive sector. Researchers like Braun et al. [BNS*14] or Smith [SG99] already apply capacitive proximity sensing in the automotive domain. These selected applications already relate to research questions RQ1 and RQ2. They are only based on existing vehicle structures. Nevertheless, these applications have problems that could also be addressed with capacitive proximity sensing, and they represent only two vehicle structures and two applications. This thesis expands the space of vehicle structures used to include steering wheels, legroom, child seats, and driver seats. The interaction provided by Braun et al. is limited to symbolic gestures. Based on the applications developed in this thesis, the gesture space is extended to other entities such as deictic gestures. Additionally, gestures in this thesis will not be based on hand gestures only. Foot gestures are also enabled in the automotive environment by capacitive proximity sensing. In addition to the technical perspective, researchers have also addressed privacy issues in vehicles. Nevertheless, these systems mainly focus on general privacy concerns. This thesis moves from a general view of sensors in vehicles or ambient intelligence to two specific sensor systems: the camera and capacitive proximity sensing. To further support benchmarking and selection of an appropriate sensor system, this thesis assesses users' subjective perceptions of privacy concerns about these systems. In addition, it was noted earlier in Chapter 2 that related research addresses privacy concerns that arise as established systems advance. This thesis puts the focus in the area of driver assistance systems, which are shown in Section 6.1. To conclude Chapter 2, I have to note that the applications of this thesis have further related work and address further issues that are present in the current circumstances of the environment of car users. Related work is therefore also part of the concept of this thesis, presented in Chapter 3. Specific required related work and topics are further presented along with Implementation Chapters 4 and 5.

# 3. Concept

In Chapter 2, research related to human machine interfaces and interaction in vehicles was presented. Research questions RQ1 and RQ2 were addressed by presenting applications and the researchers' approach to developing these systems. Special attention was paid to Braun's [Bra14] benchmarking process which will be a part of the concept of this thesis. Since research question RQ3 focuses on a specific feature of human machine interfaces, namely user privacy, related work that captures privacy concerns under specific conditions was shown. In addition, the required physical properties of capacitive proximity sensors were shown in Chapter 2. Since RQ1 and RQ2 focus on in-vehicle human machine interfaces and interaction, a concept is now presented on how to develop these systems. How the special properties of the vehicle interior can be taken into account in the development of interfaces is described in Section 3.1. Since interaction is considered as a subset of interfaces, a modification is shown how this approach can be used for human machine interaction in vehicles. Section 3.2 refers to RQ3. The assessment of privacy concerns is divided into two perspectives, which are presented in Section 3.2. On the one hand, the perspective of the law, which imposes restrictions on the development of data collection systems. On the other hand, the perspective of the user, who may have personal privacy concerns about certain sensor systems in in-vehicle human machine interfaces.

## 3.1. Developing vehicular human machine interfaces

The applied approach for the development of human machine interfaces in vehicles is shown in Figure 3.1. The concept follows the development from the idea to the evaluation. This approach shows how a vehicular human machine interface can be developed that works exclusively with existing vehicle structures and capacitive proximity sensing. The applied evaluation refers to a proof of concept using a developed prototype. We will now iterate through each step of the process.

### 3.1.1. Existing systems, current research and applicable statistics

This part of the process is labeled 1 in Figure 3.1. It can be understood as a funnel for upcoming ideas. Indeed, the current state of vehicle interface development, the challenges addressed by research and current statistics need to be studied. It is therefore important to follow progress in the automotive sector and emerging systems in other markets that could be used in cars. One example is the analysis of accident statistics. The following list shows sources for accident statistics.

- NHTSA - National Highway Traffic Safety Administration [NHT20a]
  - Detailed information on accidents in the United States; It is particularly interesting because it breaks down the causes of accidents.
- Destatis - Statistisches Bundesamt Germany [Sta20b]
  - Similar statistics like the NHTSA; Unlike the NHTSA, focus is on German incidents.

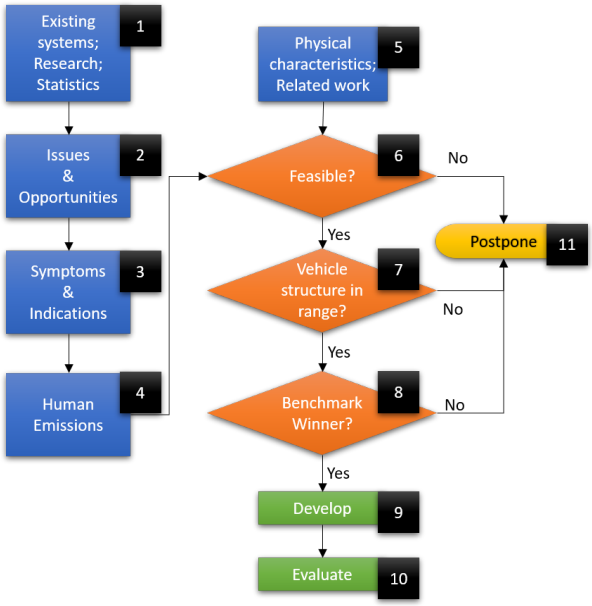



Figure 3.1.: Approach summary: from idea to evaluation

When it comes to accident statistics, ideas often refer to driver monitoring systems or to the proper use of passive safety devices such as seat belts. Vehicle manufacturers and their suppliers are also addressing these numbers by developing or adapting human machine interfaces in vehicles. The head-up display is one example of a system designed to minimize the distraction while driving. Current systems and mechanisms in vehicles are the second recommended source of ideas where capacitive proximity sensing could improve driving safety and comfort. The following list therefore shows exemplary areas of human machine interfaces in vehicles:

- Injury avoidance
  - Seat belt and restraint systems, airbags, child seats
- Authentication
  - Authentication methods like keys or biometric identification
- Attention and fatigue monitoring
  - Systems asses the physiological state of the driver to rate the current ability to control the vehicle.
- Human control
  - Ways how driver or passenger can interact with the vehicle. There are for example push buttons, gesture recognition or voice control.

### 3.1.2. Issues and opportunities

So far, this is just a vague collection of sources for ideas on developing human machine interfaces in vehicles. Step 2 of the approach puts ideas into a tangible context. This step examines problems and opportunities of existing systems or those resulting from accident statistics to form countermeasure. For example, if one cause of

an accident is fatigue, the countermeasure would be how to avoid fatigue driving in the first place. So, fatigue driving could be detected to prevent accidents. When it comes to current research and systems currently in use, there are ways to improve these systems. An example of Step 2 is injury prevention. A seat belt system can only ensure safe operation if it is worn properly. So, a system designed to improve safety could measure whether the seat belt is properly fastened. In this case, safety can be improved by interfaces that ensure proper use of the existing system. The problems are not just about the causes of accidents. Inadequate usability of existing controls can also be a problem. Therefore, systems such as gesture recognition or voice control can improve the usability of interfaces in the vehicle. Once the issues and opportunities of existing units are identified, Step 2 is completed. The list presented in Step 1 continues to Step 2 in the following list:

- Injury avoidance
  - Seat belt issues
    - Is the seat belt properly applied to occupants?
    - Is the seat belt properly fastened to occupants?
    - Are additional systems like child seats properly fastened?
  - Airbag issues
    - Does the driver not intersect with the airbag deployment area?
    - Are additional systems like child seats properly secured from inflating airbags?
- Authentication issues
  - Are existing systems like keys or biometric identification secure
    - They should only provide access to people with the right credentials
    - Is the existing system vulnerable to security breaches?
- Attention and fatigue monitoring opportunities
  - Do existing systems provide privacy secure operation?
  - Can existing systems be enhanced by measuring further symptoms of inattentiveness?
- Human control issues and opportunities
  - Gestures
  - Pointing devices
  - Replacement of existing systems with capacitive proximity sensing

### 3.1.3. Symptoms and indications

Most of the issues and opportunities in Step 2 relate directly to symptoms and indications of the human body or vehicle safety equipment. Symptoms of the human body must be collected based on a medical or purpose background. A driver fatigue detection system can only evaluate the driver's condition based on symptoms associated with fatigue. An indication is anything that the driver knows has an effect on the control system, like spoken language or hand movements that form a gesture. To give examples for Step 3, the list presented in Step 2 is continued:

- Seat belt issues
  - Is the seat belt properly applied and fastened to occupants?
    - Opportunity: The seat belt is applied as indicated concerning position at hip and breast.
    - Possible symptom: The occupant body moves very loosely while driving

        - Possible symptom: The force applied on the seat does not significantly change compared to the force applied on the seat without seat belt.
    - Are additional systems like child seats properly fastened?
        - Opportunity: Mounting of child seat is in accordance with the specifications.
        - Possible symptom: The child seat moves suspiciously while driving
- Airbag issues
    - Does the driver not intersect with the airbag deployment area?
        - Possible symptom: The driver head is located within the airbag deployment area
    - Are additional systems like child seats properly secured from inflating airbags
        - Opportunity: Deactivate airbag if a child seat is applied
        - Possible indication: There is a child seat on the seat
- Are existing systems like keys or biometric identification secure?
    - Opportunity: Provide less vulnerable authentication method
    - Possible indication: Changeable password without hand contact
- Attention and fatigue monitoring opportunities
    - Symptoms: Frequent yawning, nodding, eye close interval
- Human control issues and opportunities
    - Indication: Hand movement
    - Indication: Meaning of spoken words

### 3.1.4. Human emissions

Every symptom and indication can lead to emissions of the human body. These symptoms can be more or less measurable by using capacitive proximity sensors. Capacitive proximity sensors are able to measure changes in the electric field. The measured change depends strongly on the distances between the human body and the sensing electrode, as shown in Section 2.1.2. Symptoms and indications as analyzed in the last step must be associated with body movements. This must be done to prepare for the next step (is this feasible). However, this step is not only related to capacitive proximity sensing capabilities. Although emissions such as heart rate do not appear to be measurable with capacitive proximity sensing, a review of related research may provide clues as to how this might be possible with capacitive proximity sensing. The following list shows exemplary human emissions for the symptoms and indications mentioned in the previous step:

- Seat belt issues: The occupant body moves very loosely while driving
    - The inertia of the human body in combination with the stiffness and damping of the restraint system can lead to characteristic oscillatory movements in differently fastened seat belts.
- Seat belt issues: The force applied to the seat does not change significantly compared to the force applied to the seat without a seat belt.
    - The seat cushion should be compressed when the seat is occupied. Compression should be increased when the seat belt is in place and fastened. The squeezing should move the human body closer to the structure supporting the seat cushion.
- Seat belt issues: The child seat moves suspiciously while driving
    - Improperly installed child seats can cause suspicious vibrations while driving.

- Airbag issues: The driver's head is in the deployment area of the airbag
  - The distance between the driver's head and the steering wheel is less than a certain value that correlates with the deployment range of the airbag. The same can apply if the driver's head is too far away from the headrest. In this case, the distance between the airbag deployment area and the headrest must be known.
- Airbag issues: Are additional systems such as child seats properly secured from inflating airbags?
  - The installation of a child seat, whether rear-facing or not, can change the electrical characteristics of the child seat environment.
- Are existing systems such as keys or biometric identification secure?
  - A secure system could measure the hand gesture indicating a password like a signature.
- Attention and fatigue monitoring opportunities: Yawning, nodding
  - Yawning can cause movement of the human chest or back. The movement of the human chest or back changes the position of the human body, which can be measurable.
  - Nodding in refers to head movements. Similar to the airbag out-of-position measurement, the head position and speed of head movement should be a measurable emission.
- Attention and fatigue monitoring opportunities: Eye close interval
  - The movement of the eyelid may cause changes in the color of the facial area.
- Human control issues and opportunities: Hand movement
  - The position and speed of the hand, in this case, is the human emission.
- Human control issues and opportunities: Meaning of spoken words
  - The human speech consists of specific acoustic frequencies.

### 3.1.5. Physical characteristics; related work

Step 5 is required to prepare Step 6, as shown in Figure 3.1. The human emissions identified in Step 4 may relate to specific characteristics of capacitive proximity sensing. First, related work of electric field sensing application must be studied with respect to human emissions. This is necessary to prevent human emissions from being omitted from a feasibility study, even though they may still be achievable with capacitive proximity sensing. Chapter 4 shows an example of a human emission that would probably be discarded because it seems difficult to measure with capacitive proximity sensing: heart rate. Related work shows that the heartbeat leads to movements of the human chest, which can be measured with a short-range radar. Due to the physical properties of electric field sensing, the movements of the human body can be measured. To find related work that can help evaluate the feasibility of measuring a human emission, sensor systems that measure similar entities can be investigated. For example, these related sensor systems should measure positions of the human body. These systems could be depth cameras, radar systems, pressure sensors, laser rangefinders, or strain gauges.

### 3.1.6. Feasible?

Step 6 is the point of initial decision whether to continue or postpone the project. The question is whether the combination of human emissions, related work, and physical properties will provide information indicating that a future prototype based on capacitive proximity sensors will be able to detect the human emissions found. The following list shows an example decision process:

- Related work shows a system based on capacitive proximity sensing in the automotive environment capable of measuring the selected human emissions
  - Yes, this is feasible. This project will nevertheless provide only limited new contributions.
- Related work shows a system based on capacitive proximity sensing capable of measuring selected human emissions. The presented system is not implemented in an automotive environment.
  - Yes, if it can be expected that the application shown can be transferred to an automotive environment. In order to assess the feasibility of the transfer, spatial conditions must be taken into account.
- Related work shows a system based on another sensor system which measures similar human emissions in the automotive environment.
  - Yes, if the required measurement resolution can be covered by the capacitive proximity sensing technology
- Related work shows a system based on a sensor system that measures similar human emissions outside a vehicle environment.
  - Yes, if human emissions are still visible in an automotive environment under the constraints of the previous point.
- Related work does not show a system based on a sensor system that measures similar human emissions.
  - Yes, if human emission is based on body motion where the resolution of capacitive proximity sensing is sufficient.

### 3.1.7. Vehicle structure in range

If the last step was answered with yes, we can now search for a suitable vehicle structure. This is especially important if the required application, in related work on capacitive proximity sensors, in vehicles, has not yet been addressed. To find a suitable vehicle structure, one must identify the element of the human body that is to be measured. In terms of gesture recognition, this could be the human hand. Vehicle structures within range of the body part are not the only limitation. It must also be possible to operate the system in a meaningful way. Again, regarding the hand gesture system, the passenger seat could be a suitable vehicle structure within reach of the driver's hand. However, with the passenger seat occupied, the system function would fail. It is also worth considering whether hand gestures in the passenger seat are a natural way to interact. The following list identifies example vehicle structures that are considered suitable for designated human body entities:

- Head movement
  - Head restraint
  - Steering wheel in terms of out-of-position detection, if the sensing electrodes can be mounted without affecting the operation of the airbag system.
  - Car pillars, if the head movement against a pillar in an accident is to be measured
  - Vehicle roof, if the resolution of the capacitive proximity sensors used is sufficient for the measurement in relation to the maximum distance between the inner roof and the head.
- Breast movement, e.g., for measuring the respiratory rate
  - Seat belt system
  - Back rest of the seat including side cushions
- Leg movement
  - Seating

- Foot movement
  - Vehicle legroom
  - Pedals
- Hand movement
  - Shift knob
  - Steering wheel
  - Armrest
  - Vehicle doors
  - Head down display
- Arm movement
  - Seat side cushions
  - Steering wheel
  - Shift knob
  - Vehicle doors

### 3.1.8. Benchmark winner?

After a suitable vehicle structure has been selected, the next step is benchmarking. A benchmarking model for sensors in smart environments is presented by Braun [Bra14, pp. 47–61]. The method is considered to distinguish whether the development based on capacitive proximity sensing is suitable or not. Therefore, it is included in the concept of this thesis. The benchmarking model has already been presented in Section 2.3. To apply the benchmarking model, the feature matrix for the selected sensor systems must be estimated according to Table 2.1. One must define weights for metrics such as sensor resolution, update rate, unobtrusiveness, or unique limitations. Similarly, application weights must be defined. The application weights rate the importance of the sensor features as shown in Table 2.1. The benchmarking score can then be calculated. The final score is tied to the application. Only sensors for the same application can therefore be compared with the benchmarking score.

Based on the research questions RQ1 and RQ2, several constraints are introduced. Steps 6 and 7, already include the boundary conditions for the use of capacitive proximity sensors, as shown in Figure 3.1. Capacitive proximity sensors must be able to measure the events of the application based on their physical principle. The design influence and thus the obtrusiveness should be as low as possible. An existing vehicle structure is therefore to be used as a carrier for the sensor system. These constraints are also applied to other sensor systems. The feature matrix of the sensor is now detailed by the combination of the sensor system and the designed mounting method including the vehicle structure. This makes it possible to evaluate several vehicle positions separately in combination with the sensor system. A consequence of this change is that some of the metrics proposed by Braun change and become exclusion criteria. The weights for the metrics have also been adjusted. Only if properties of a sensor system that are better than required lead to an improvement of the system, this metric gets a weighting. Otherwise, it remains a pure criterion for exclusion. The metric is also made more quantifiable by adding additional criteria to the metric definition. Steps 5 to 7 are also applied to all combinations of sensor systems and vehicle structures. An example is provided to illustrate the changes. The exemplary application is nodding detection to support driver drowsiness detection. Nodding off is related to head position as a human emission and its derivative over time. The candidate sensors are capacitive proximity sensors, pressure sensors, and cameras. The selected candidates for vehicle structures are the headrest and the steering wheel. This results in the following combinations of application and detection ranges:

- Head restraint: $\approx 5 - 42cm$
- Steering wheel: $\approx 5 - 42cm$
- Steering wheel + head restraint: $\approx 5 - 21cm$

In this example, the detection range is not only an exclusion criterion. The nodding motion could also be detected with smaller ranges if the initial motion characteristic of nodding is sufficient to distinguish between nodding and normal head motion. A larger detection range than required is unlikely to result in a better system. Based on the detection range, sensors can be examined in terms of their physical characteristics. A pressure sensor can only detect changes when it is touched. It is likely that none of the vehicle structures will be touched by the head when it nods off. Therefore, the pressure sensor can be excluded. The remaining sensors are cameras and capacitive proximity sensors. The next metric considered is resolution. The expected duration of a nodding event is about one second. Consequently, the measurable velocity should be about 37 cm/s. We do not yet know the characteristics of the nodding event, but a resolution of about 2 cm seems reasonable. This is only an estimate, since we do not know if lower or higher resolutions could also detect head motion. In this case, the resolution metric remains an interval from lower to higher resolutions. Higher resolution will likely improve the measurement of head position, while lower resolution should at least increase the processing overhead.

The next metric considered is the update rate. As mentioned before, the measurable speed should be around 37 cm/s. Now, the sampling rate should be at least greater than the Nyquist frequency, which is two times the maximum frequency of a nodding event. Thus, to measure a nodding-off event, a sampling rate of at least 2 Hz is required. Higher frequencies, up to ten times the maximum frequency, should receive better weighting. Frequencies greater than ten times the maximum frequency should not contribute any additional information and therefore are not given better weighting. The update rate is also an interval and an exclusion criterion. Sensors that have an update rate lower than the minimum are excluded. In this example, both sensors provided update rates greater than required. The subsequent metric, unobtrusiveness, is quantified for this thesis. The weighting of this metric with respect to application remains the same as in Braun's model. In contrast to Braun's proposal, the sensor value is adjusted. Each sensor starts with a score of (++). Then the value is lowered whenever the sensor system encounters one of the following points. The first point is privacy. A definition of data collected that poses a threat to privacy is included in the GDPR. A system that violates these definitions will be downgraded one point. The system will also be downgraded if it cannot be invisibly integrated into the vehicle structure and if it must be mounted as an additional device on the vehicle structure. The final downgrade relates to Braun's proposed measures. The system is downgraded if it restricts the user's field of vision. We now continue with the example of detecting nodding off. To detect nodding off, a camera needs a line of sight to the head. It must therefore be visible to the driver. The rating is reduced by one. A camera that monitors the driver's head, which is required in the field of view, is a privacy threat: facial images (GDPR [Cou16], Article 4, Paragraph 14). The rating is therefore reduced by one to a rating of "o". If the camera can be integrated into the steering wheel, it should not restrict the driver's field of vision. Therefore, the value is not reduced. However, if it were installed in the windshield, it would restrict the field of view and would therefore be reduced. Capacitive proximity sensors neither restrict the field of view nor directly interfere with the GDPR. Their rating therefore remains at "++". Braun describes the processing complexity metric as a metric that describes the required processing power of the system. This metric remains unchanged. Latest processing units for vehicles show the ability to perform real-time processing of multiple cameras and other sensors [Ros20]. This ability for high processing performance makes processing complexity seem more like a measure of cost. Another metric, robustness, is described by Braun as a criterion for quality of service. The actual weighting of robustness is a matter of application. A system that has to be managed according to ISO 26262 [Int18] should nevertheless result in the highest weighting number. The remaining metrics disturbance frequency and calibration complexity remain untouched. The metric unique limitations is changed to an exclusion criterion.

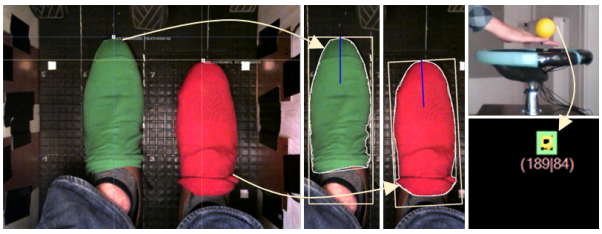



Figure 3.2.: Using motion trackers for automatic labeling of data.

### 3.1.9. Develop

The outcome of the previous steps is whether the application with capacitive proximity sensing is superior compared to other sensor systems. Now we look at a guide to best practices gathered in the development of human machine interface applications in vehicles with capacitive proximity sensing. The development is divided into several domains. The first area is the use of the vehicle structure, which was selected in Step 7. The vehicle structure is utilized by placing sensing electrodes on it. If possible, the sensing electrodes should be integrated invisibly into the vehicle structure. These sensors can sense through non-conductive material. The ability to integrate the sensors invisibly is therefore independent of a vehicle structure being covered with or made of non-conductive material. The geometry of the structure also limits the shape of the sensing electrodes in space and curvature. It has been our experience that the use of solid copper electrodes shows the best results. Nevertheless, these electrodes are only used in scenarios where the vehicle structure has sufficiently flat surfaces, as in the foot tracking scenario in Section 5.3. Other scenarios, such as head position detection where the sensing electrodes are placed under the headrest cover, as shown in Section 4.1, require flexible electrodes. In this case, self-adhesive copper foil is applied to flexible plastic material. The sensor material is readily available and inexpensive. We use at least eight sensing electrodes in all scenarios. Only the application shown in Section 4.1 requires 16 sensing electrodes. In all cases, the sensing electrodes are distributed within the selected vehicle structure so that the objects to be sensed are enclosed. Each sensing electrode should be accompanied by a congruent shield to allow directional measurement.

We will next talk about labeling the data. This step is critical because it is not easy to subsequently label data from capacitive proximity sensors. Correct labels are the basis for analyzing the acquired data to build an expert system or to train a regression or classification model. In this thesis, several labeling methods are used. The first method is manual labeling which is often used in classification tasks. The procedure can be carried out without additional sensors if the classes to be distinguished can be sufficiently distinguished from each other during the measurement. An example is occupancy recognition. If the subject is unable to assume certain positions, additional sensor technology can be used to label the data. For example, the labeling of sleep states for the child in Section 4.2 is done using an additional camera which monitors the subject. In this case, the data from the camera and the capacitive proximity sensors are acquired synchronously. The video data is then manually analyzed to extract the time intervals during which the child is asleep or awake.

Manual analysis of video data can be tedious. Especially when the target application refers to multiple classes that need to be distinguished. This problem is exacerbated in regression problems with continuous targets. In this case, motion trackers are applied to the observed limb of the subject. Two examples of attached motion trackers are shown in Figure 3.2. In both cases, specific colors are applied to the objects to be tracked. For feet of the object, coatings with different colors are used. The application is shown in Figure 3.2. Since color markers are attached to the person's feet, the foot position can be measured within the video data. Then the capacitive

Figure 3.3.: Using additional sensors for automatic labeling of data.

proximity sensing data can be labeled with the actual foot position. Another example is shown on the right side of Figure 3.2. A yellow ball attached to a ring is used in the right application. In this application, the position of the hand must be tracked. In both examples, the images are filtered by the associated colors (green, red and yellow). Then a rectangle with minimal area is fitted to the contour of the filtered color. The center of the rectangle is used as the label on the right side of Figure 3.2, while the top center of the rectangle and the angle are used as the labels on the left side of Figure 3.2.

A camera is not the only sensor that can be used for automatic labeling. Various applications require other sensor systems to label the data. One example is the rotation speed of the steering wheel. A rotation speed sensor is therefore attached to the steering wheel, as shown in Section 4.1. With this sensor, the data of the capacitive proximity sensors can be labeled directly. The setup is shown in the graphic in the top left of Figure 3.3. An additional example is shown on the right of Figure 3.3. To measure the heart rate of the subject in the child seat, an optical heart rate sensor is attached to the subject. Using sensors that directly measure target variables is better than using indirect measurement systems such as evaluating cameras. The measurement error of the target variable is then based solely on the measurement error of the sensor used and not additionally on processing methods such as color filters.

Additional sensors may be appropriate for monitoring the environment of the test setup. In particular, the vehicle interior can be subject to strong temperature fluctuations due to air conditioning systems. An additional temperature sensor is added to the system presented in Section 4.2. The temperature sensor records the absolute temperature before the vehicle is started (i.e., without air conditioning) and during the test drives (after the air conditioning has equalized the temperature in the vehicle). To show influences of the temperature, an example from practice is chosen. It is based on the child seat application shown in Section 4.2. In this application, eight sensing electrodes are installed in a child seat. More than 600 km of data is collected on the roads at different ambient temperatures. The minimum value of all capacitive proximity sensors, during the test drives, is shown in Figure 3.4. The legend refers to the test run number. The curve of the measured values as a function of temperature shows a correlation between temperature and sensor offset. Temperature changes from 20°C to 40°C result in capacitive proximity sensing value increase of over 1,000. This is between 3.8% and 60.5% of the channels observed measurement range (60.5%, 31.4%, 56.6%, 13.3%, 3.8%, 16.9%, 6.9%, 4.4%). Temperature sensors could be added to the final system and included in the classifier. We will, however, show later in this section how possible temperature influences can be reduced by preprocessing the data. Before showing ways to remove temperature influences, basic preprocessing steps are presented. These preprocessing steps form the basis for further analysis, e.g., with machine learning models. One of the first filters which are applied in applications

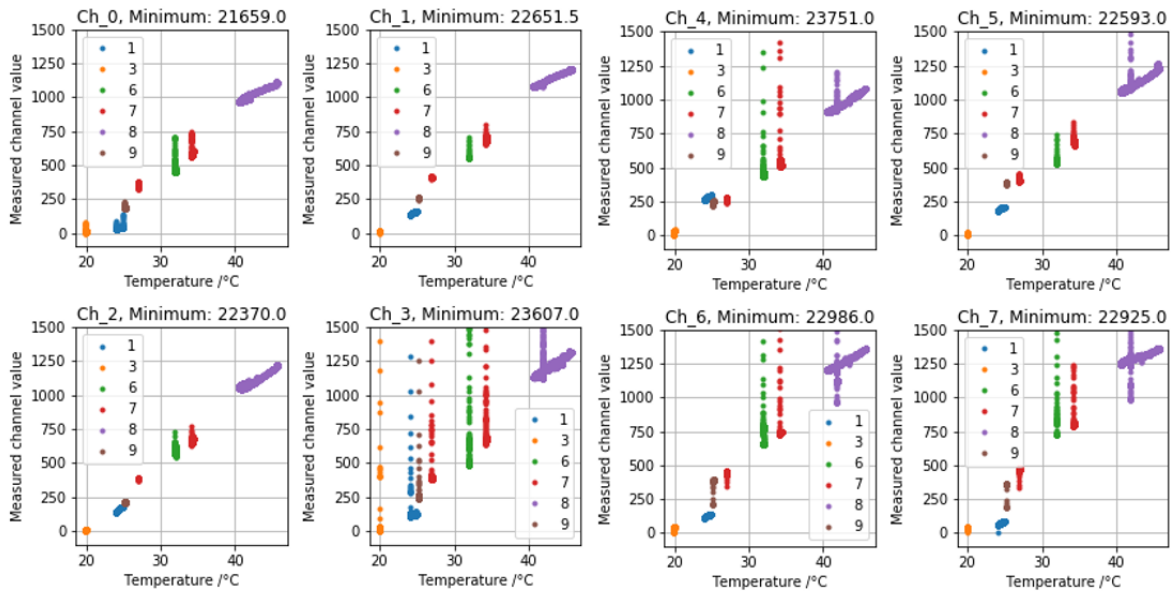



Figure 3.4.: Raw minimum capacitive proximity sensing output at different temperatures.

of Chapters 4 and 5 is a median filter. A median filter uses a window (kernel) to process data. The window size refers to the number of samples to be filtered. All samples within the window are sorted by their value. Then the value in the middle of this sorted window is selected as the new value at the timestamp of the window. This filter can handle spikes in the measurement data. MinMax normalization is also frequently used in this thesis. The result is that the sensor values are placed on a scale between zero and one. This normalization is especially recommended when the sensing electrodes of the system are covered by different cushion thicknesses, as shown in Section 4.2. Different cushioning influences the measuring range. The minimum value is usually a system without object. The maximum value is usually the value when the subject is closest to the measuring electrode during execution. The output value can therefore be related to the detection range of the sensor.

$$V = X + O(\vartheta, g) \tag{3.1}$$

As already shown, temperature can have an influence on the output of capacitive proximity sensors. Processing steps are now presented on how to reduce the temperature influence. In particular, if the sensor array is distributed around the object, one can use the ratio between the sensors to reduce the temperature influence. The following considerations are already applied in the project shown in Section 4.2. The preprocessing steps are applied in particular to the position detection of the child's head in the child seat. In this application, a model for the measured value of capacitive proximity sensors is based on Equation 3.1. The emitted sensor value ($V$) is composed of a distance-based value $X$ and an additional value $O$. $O$ depends on the sensing electrode geometry ($g$), temperature ($\vartheta$), moisture, geometrical deformation and dielectric changes. If a rigid vehicle structure is used, the geometric deformation is neglected. In further processing, $O$ is only considered as a function of temperature and geometry. These reductions lead to Equation 3.2. $O$ is split into temperature ($T$) and geometry ($G$) addends.

$$V = X + T + G \tag{3.2}$$

In the case of the application in Section 4.2, all sensing electrodes used have the same geometry. Since the geometry of all sensing electrodes is the same, it is assumed that the changes in $T$ are the same for all sensing electrodes. This leads to Equation 3.3. The indices $m$ and $n$ represent the sensing channels.

$$\frac{dT_m}{d\vartheta} = \frac{dT_n}{d\vartheta} \tag{3.3}$$

Due to Equation 3.3, differences between $T$ among channels are constant. This relation is shown in Equation 3.4.

$$T_m - T_n = K = constant \tag{3.4}$$

Influence by geometry ($G$) is assumed to be constant ($G_m - G_n = L = constant$). Even if the differences of $O$ between channels and among measurements at different temperatures are constant, $X$ varies from channel to channel depending on the distance to the object. $X$ is the required quantity. $V_m$ and $V_n$ are therefore subtracted as shown in Equation 3.5.

$$V_m - V_n = X_m - X_n + K + L \tag{3.5}$$

Equation 3.5 is solved for $X_m - X_n$ as shown in Equation 3.6.

$$V_m - V_n - K - L = X_m - X_n \tag{3.6}$$

Unknown constants $K$ and $L$ are given in Equation 3.6. While the true value of these variables may be unknown, they remain approximately constant at different temperature levels. Due to this independence of temperature, the left-hand side of Equation 3.6 can be used for further position detection processing. A similar approach is used in Section 5.1 as the basis for a feature vector for a regression model.

In another preprocessing step, which has shown good performance in experiments, features are extracted from the frequency spectrum of the output of the capacitive proximity sensors. In particular, when frequencies are to be detected, e.g., for heart rate detection as in Section 4.2, the frequency spectrum is a suitable basis for feature extraction. A spectrogram of the measurement data can be used to remove high or low frequencies and focus the information within the data on the frequencies that are significant to the application.

Based on these preprocessing steps, a model can be designed that provides the required features for the application. Due to the nonlinear nature, all models in this thesis are based on ordinary machine learning algorithms. Regardless of whether the data collected has a nonlinear class distribution, the classifiers and regression models are based on support Vector machine, random forest, or neural networks. Model selection is closely related to evaluation. Often several models are designed and evaluated. Then, the model with the best performance is selected. The selection is not only based on the type of model, but also varies in parameters such as the number of hidden layers in neural networks or the number of estimators in a random forest model.

### 3.1.10. Evaluate

The evaluation strategy is the final step in the process. Here we assume that a prototype has already been created and is available to collect data for parameterization and validation. Since all models in this thesis are based on

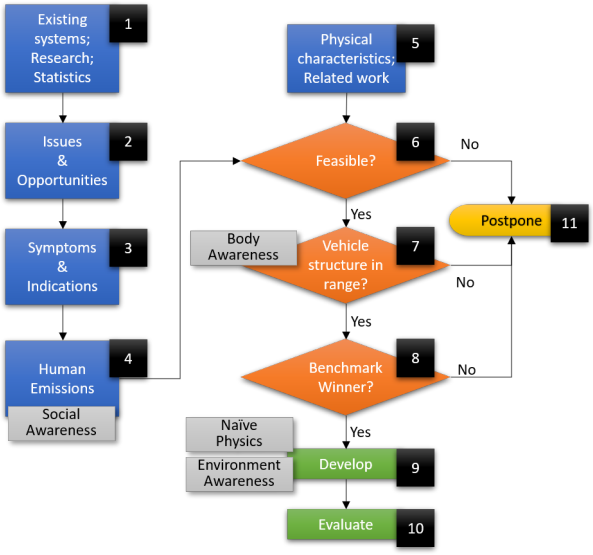



Figure 3.5.: Approach modification

machine learning models, common metrics are applied, such as those summarized by Flach [Fla12]. For classification problems, these are, for example, the true-positive rate, the true-negative rate and the coefficient of determination or the mean absolute error for the regression. In addition to the evaluation metrics, one must also consider the validation strategy. Commonly used validations include tenfold cross-validation or splitting training and testing in some ratio. A leave-one-participant-out evaluation can provide insight into the performance of the model with new subjects. However, it is difficult to assess the latter metric in evaluations with few participants. Thus, a significant number of participants must be collected. When a user study is conducted, there is an opportunity to capture the user's personal perception of the system. It is of interest whether the user likes the application and would use it in the vehicle. This can be captured in a questionnaire that is conducted after the experiment has been carried out.

### 3.1.11. Modifications for vehicular human machine interaction

In Section 3.1, the user did not even have to be aware that her or his behavior was being captured by a system. All the information needed could be derived from her or his usual behavior. We are now expanding the concept to include interaction requirements. Simple keys are interaction devices as well as the touchscreen of the head unit. Because of this variety of interaction methods, the domain of interaction is narrowed down to a limited subset of paradigms. The device for interaction is to be integrated invisibly into an existing vehicle structure. Thus, this approach is related to ubiquitous computing as presented by Mark Weiser [Wei99]. In this thesis, however, no ubiquitous networks are implemented. The focus is on using existing vehicle structures so that the integrated sensors are invisible to the user.

To describe the approach to deriving a concept for vehicle-user interaction to answer research question RQ2, a brief overview of the history of human machine interaction will clarify the goal of the concept. According to van Dam [vD97], the evolution of user interfaces follows the use of punch card input to command line-based shell

interfaces to WIMP (windows, icons, menus, and a pointing device) graphical user interfaces. WIMP interfaces are the common applications on desktop computers. WIMP interfaces made computers usable for many people without a computer science background. Van Dam also says that the success of these interfaces is based on how easy the interface is to use. This is seen as an advantage of WIMP interfaces over shell-based interfaces. Van Dam also describes how these interfaces are still an intermediate layer between the user's intentions and the actual input to the computer. Van Dam states that the ideal interface is no interface. Additionally, the user's interaction should be based on natural human behavior such as speech, gestures, and facial expressions. The goal of this thesis is therefore to enable natural user interfaces in vehicles. The focus will be on human gestures or body postures, as these change the position between the sensor and the human body. It is very unlikely that capacitive proximity sensors can be used in an application where they pick up human speech or facial expressions. Regardless of whether speech control is required, they can still be part of the application and form a multimodal interaction device. In order to provide a guideline for the development of a vehicle-human machine interaction based on capacitive proximity sensors, the projects are embedded in a framework for reality-based interaction according to Jacob et al. [JGH*08]. Jacob et al. name several entities which are present in reality-based interaction: *Naïve physics*, *body awareness and skills*, *environment awareness and skills* and *social awareness and skills*. *Naïve physics* is based on the shared understanding of the driver and other users of the vehicle of how the physical world works. *Body awareness and skills* means that the driver or passenger is able to locate entities of his or her body. This includes the anthropometric conditions of the user. *Environment awareness and skill* means that the driver and passenger are aware of the physical environment. Specifically, this refers to the physical entities of the vehicle interior and the entities in the driving scene, such as traffic ahead or road conditions. The final element is *social awareness and skills*. This refers to communication between people. Communication can be verbal and nonverbal. Based on the framework of Jacob et al. a common approach for the development of capacitive proximity sensing for human machine interaction in vehicles is derived for this thesis:

- *Naïve physics*
  - The proposed interaction should be plausible in sense of basic physical characteristics.
- *Body awareness and skills*
  - The proposed interaction has to consider the anthropometry of the user in the vehicle.
- *Environment awareness and skills*
  - The interaction interface should be based on existing elements in the user's environment. In particular, this is interpreted as using existing vehicle structures and extending existing information such as traffic or road conditions when the environment plays a role in the interaction application.
- *Social awareness and skills*
  - The interaction provided in the vehicle should take into account the cognitive load of the user. The interaction should be based on analog communication and the behavior of the driver or passenger without unnecessarily introducing new communication techniques. Regarding capacitive proximity sensing in vehicles, gestures related to human-to-human communication should be the basis for interaction.

In summary, this means that the interaction device should be based on the existing physical characteristics of the driver or passenger. Developed methods such as gesture recognition should be based on the driver's natural communication or behavior and introduce few new interaction commands that need to be learned. In addition, provided interaction interfaces should not only address issues of accident statistics or related work, but should at least provide an idea for an interaction application. The interaction application should elaborate how the provided interface can help with multimodal interaction and enable new features for natural interaction. The interaction development framework is applied in several stages of the concept presented in Section 3.1. Each framework


Figure 3.6.: Example interaction gesture

entity is added to the concept as shown in Figure 3.5. *Social awareness and skills* is added to human emissions, as opportunities for natural interaction must be found at an early stage of development. If natural interaction is not possible at this stage, it would be necessary to reconsider whether the application significantly supports the vehicle user. *Body awareness and skills* is added to the vehicle structure item. The anthropometric conditions of drivers or occupants are already taken into account at this stage, since the vehicle structure must provide the occupants' capabilities for interaction within reach. *Naïve physics* and *environment awareness and skills* are also added to Step 9: Develop. Whether the application is based on the user's physical perception is part of the application design and should therefore be considered if the previous steps have already been performed. The system's contextual awareness of the environment is also part of the development. Even if the framework entities are dedicated to several steps of the concept, contributions to these entities may also occur in the other steps. For example, if the capabilities in Step 2 already indicate multimodal interaction that requires contextual information, so capacitive proximity sensing could be just one part of the system.

**Example:** The process is illustrated with an example. There are some prerequisites. This example is a thought experiment and does not necessarily address existing problems. The basic prerequisite is that the driver should be able to control the vehicle interior with natural communication. In this particular example, the driver should be able to control the multimedia system in the back seat. This could be done with voice commands. However, if the context for the speech is unknown to the system, it could be difficult to understand the specific commands to be spoken. Therefore, this could affect the *social awareness and skills* paradigm, as the system would unnecessarily introduce new commands. This points to a multimodal approach similar to presented by Bolt [Bol80]. The speech interface should therefore be supported by hand gestures to form a multimodal interaction interface. A pointing gesture is chosen because this form of interaction is already common among young children [BI00]. This application therefore refers to deictic gestures. Deictic gestures are pointing gestures to objects while speaking to give context to the speech. An exemplary gesture in combination with a command is shown in Figure 3.6. The driver moves his hand up and points with the thumb towards the backseat. Additionally, he speaks the words *Calm Down!*. If the system is able to put this combination into context, targeted control can be provided. For example, there could be children in the back seat. In this case, the vehicle could switch on multimedia devices in the back seat. In another context, an autonomously driving vehicle could change lanes because the driver feels disturbed by an approaching vehicle. Because the system is based on natural interaction, the point *body*

*awareness and skills* is covered. The driver needs not to perform any unusual gestures. Additionally, the point *environment awareness and skills* is addressed because the driver can interact directly with the environment. The vehicle would nevertheless also have to monitor the environment in order to detect the context. The development of context detection is not the subject of this thesis. This thesis is about the technical feasibility of the interaction based on capacitive proximity sensing. The concept for the development of the sensor topology, the selection of the vehicle design, and the benchmarking has already been presented in Section 3.1. To complete the thought experiment, the human emission is the hand movement of the driver. Specifically, the movement of his hand toward the rear seat. Object positions can be estimated with capacitive proximity sensing, as shown in Section 2.1.2. The hand position refers to specific movements, so the requirements of the application could be enabled by capacitive proximity sensing. Vehicle structures within range are the interior roof and seats. It is unclear whether this approach would win benchmarking, as competing sensors such as radar or infrared sensors could better enable this. Development and evaluation would require capacitive proximity sensors to be installed in the interior roof and seats to collect data for training and evaluation of an appropriate processing model.

## 3.2. Approach to capture privacy concerns

We now discuss how we can contribute to research question RQ3. Research question RQ3 concerns privacy and thus the handling of personal data. Human machine interfaces in vehicles need to collect data from the user. The collection of personal data may raise privacy concerns. Legislation addresses this by adopting regulations. Existing systems can be analyzed based on laws. Regulatory-based analysis is the first step of this approach. It addresses research question RQ3 from the perspective of the law. The process for capturing privacy concerns from a legal perspective is shown in Section 3.2.1. Section 3.2.1 is based on *Privacy by Design: Analysis of Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces* [FK20b]. Nevertheless, processes that are considered to be of data protection concern from a legal perspective do not necessarily reflect the user's perspective. Another concept must be used to capture the user's perception. This concept is presented in Section 3.2.2. Section 3.2.2 is based on *Privacy by Design: Survey on Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces* [FK20c]

### 3.2.1. Privacy concerns from a legal perspective

Threats to privacy are assessed based on the analysis of data collected by existing systems in research and production. Before systems can be analyzed, a definition of privacy has to be determined. The definition of privacy refers to the legal perspective. To be precise, it is about the General Data Protection Regulation (GDPR) of the European Union [Cou16]. The GDPR applies to 447,706,200 people [MM20] (EU, 27 countries without U.K., January 1st 2020). The GDPR is not specific in terms of automotive sensors. Nevertheless, the European Data Protection Board (EDPB) has issued guidelines for the processing of personal data in relation with connected vehicles and mobility-related applications [EDP20]. According to the EDPB, the GDPR applies to processing of sensor data in vehicles due to the following circumstances: Vehicles become massive data hubs that collect and record driving habits, locations, the driver's eye movement, pulse or other biometric data. The majority of data generated by a connected vehicle can be considered personal data. According to the EDPB, the GDPR applies in all cases where personal data of individuals are processed in a connected vehicle. The term "connected vehicle" refers to vehicles with electronic control units linked together via an on-board network as well as the ability to share data with devices outside the vehicle. For this reason, connected vehicles are regarded in the GDPR as terminal equipment such as a computer, a smartphone or a smart TV. The EDPB explicitly includes systems such as fatigue detection in vehicles.

Data protection by design and by default is demanded by the GDPR (GDPR, Article 25: *"Data protection by design and by default"*). The EDPB states that this article has to be applied to vehicular human machine interfaces. Specific instructions about the local processing of personal data are provided by the EDPB. If the personal data is processed in a processor or controller, the GDPR also applies. Now that the GDPR can be applied to vehicles, the GDPR definition of personal data and thus the definition of threats to privacy can be introduced. In summary, biometric data refer to the feasibility of identifying individuals, profiling refers to tracking and predicting the behavior of individuals and genetic data refers to inferring the physiology or health of individuals (health is included in the GDPR, Article 4, paragraph 15). Subsequent references to privacy refer to this definition. Collection of such data is considered a possible threat to privacy. This definition of personal data follows GDPR Article 4:

> ***'personal data'*** *means any information relating to an identified or identifiable natural person ('data subject'); an identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person;* (GDPR, Article 4, Paragraph 1)
>
> ***'biometric data'*** *means personal data resulting from specific technical processing relating to the physical, physiological or behavioural characteristics of a natural person, which allow or confirm the unique identification of that natural person, such as facial images or dactyloscopic data* (GDPR, Article 4, Paragraph 14)
>
> ***'profiling'*** *means any form of automated processing of personal data consisting of the use of personal data to evaluate certain personal aspects relating to a natural person, in particular to analyse or predict aspects concerning that natural person's performance at work, economic situation, health, personal preferences, interests, reliability, behaviour, location or movements* (GDPR, Article 4, Paragraph 4)
>
> ***'genetic data'*** *means personal data relating to the inherited or acquired genetic characteristics of a natural person which give unique information about the physiology or the health of that natural person and which result, in particular, from an analysis of a biological sample from the natural person in question* (GDPR, Article 4, Paragraph 13)

The approach of this thesis, how systems on privacy concerns are analyzed, is based on the demand for "privacy by design and default" (GDPR, Article 25: *"Data protection by design and by default"*). To do so, systems are assessed by their sensor system and task. This is called "Purpose". Sensor system and application may provide further opportunities to assess for example personal data. This is called "Opportunity". The difference between Purpose and Opportunity is selected as a metric for privacy threats when the opportunities relate to personal data. This difference will be called "Purpose - Opportunity - Difference". For example, human machine interfaces are intended for a specific task that is made possible by sensor data processing. If opportunities to derive more information from data as needed are present and the additional information interfere with the definition of privacy, "Purpose - Opportunity - Difference" is given. This difference is analyzed by comparing the human machine interfaces of vehicles with systems which cause privacy concerns. Both systems have to rely on similar sensors. The analysis is shown in Chapter 6. The idea for this measure emerged partly due to the literature of McDonald et al. [MC05] where established technology advances and starts collecting sensitive information.

**Explanatory example:** An interior camera is used by Rezaei et al. [RK14]. The driver's attention, especially nodding off due to fatigue (Figure 3.7, left), is recorded. A similar sensor design, which also evaluates camera shots of the driver's head, is used by Su et al. [SC19]. Driver behavior like smoking and mobile phone usage is recognized by Su et al.. While the purpose of the system of Rezaei et al. is to measure head nodding, the

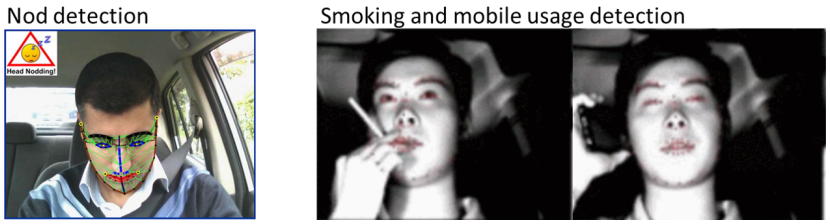



Figure 3.7.: Left: nod detection [RK14], right: smoking recognition [SC19]

captured data provides opportunities for profiling or health estimation, as used by Su et al.. Due to this "Purpose - Opportunity - Difference", profiling can become an issue that challenges the "privacy by design" paradigm.

### 3.2.2. Privacy concerns from the user's perspective

We discussed legal protection of privacy in vehicles and the approach to analyze existing systems in research and production in Section 3.2.1. Nevertheless, as shown in Section 2.4, the perception of users' personal feelings towards privacy may differ from the legal definition. Privacy concerns of different sensor systems in vehicular human machine interfaces of the user are investigated in a separate study. The basis of this study is formed by three hypothesis that have emerged from the analysis of vehicular human machine interfaces. The basis for forming these hypotheses is described in Chapter 6. The hypotheses are directly related to the comparison between camera-based driver assistance systems and those based on capacitive proximity sensors. Although the deduction of the hypotheses has not yet been described here, they are mentioned here to illustrate the process of creating the survey:

> **Hypothesis H1**: *If a vehicular human machine interface includes a camera that captures images of passengers, then people have privacy concerns about the vehicular human machine interface.*
>
> **Hypothesis H2**: *If a vehicular human machine interface is based on capacitive proximity sensing and therefore does not capture a picture of passengers, then people have fewer privacy concerns about the vehicular human machine interface compared to camera-based systems*
>
> **Hypothesis H3**: *If a car user has to choose between camera-based vehicular human machine interfaces and capacitive proximity sensing-based vehicular human machine interfaces, then they will prefer the capacitive proximity sensing-based system*

The concept of this topic consists of the design of a questionnaire. The relevant parts for the design of a questionnaire follow Hollenberg [Hol16]. As stated by Hollenberg, the target group has to be defined before the questionnaire can be designed. The target group is shown in Section 3.2.2.1. One key point is the motivation of participants [Hol16, pp. 1–3]. People shall be motivated to take the survey. An essential part is that the participants understand the topic. How people should be motivated and how the topic must be introduced is shown in Section 3.2.2.2. In order not to influence the participants, the design of the questions must be carefully chosen. The question design is shown in Section 3.2.2.3 and is based on [Hol16, pp. 5–10]. The design of the survey introduction, which should lead to a comprehensible questionnaire is described in Section 3.2.2.4. Although the design of the questionnaire is carefully selected, people who are not involved in the project should review the questionnaire. This is presented in Section 3.2.2.5.

#### 3.2.2.1. Target group

The questionnaire is intended to collect significant results. For this purpose, the target group must be represented in the data. In summary, the target group is limited to German car users. This narrowing of the target group is done to capture evidence for the hypotheses in one nation. Even though the GDPR applies to 27 countries in the European Union, the participants' feelings towards privacy may differ from country to country. This is further an exploratory study which should refine the hypotheses. Still the target group German car users is not little. Follmer et al. [FG19] show that there are plenty of German car users. It is therefore expected that many of the respondents recruited in Germany are car users and thus belong to the target group. Despite the fact that the target group is limited to German car users, there is a diversity in terms of age, gender and place of residence.

In order to obtain information about whether the participant belongs to the target group, participants are first asked about demographic conditions. People are asked how often they use a car as a passenger or driver. In addition, the participants can assign themselves to an age group. The age groups cover the range from 15 years to over 65 years. Each age group has an interval of five years. Participants are asked if they live in Germany. Moreover, the distribution of the questionnaire is measured by asking the test persons about the federal state in which they live. A participant is considered to be within the target group when he or she lives in Germany and uses a car more or equal to once a year.

#### 3.2.2.2. Motivation and understanding of the participants

Following the proposal of Hollenberg [Hol16], the motivation for participants to complete a questionnaire can be derived from several parameters. One parameter is whether the questionnaire is significant to the participant. This refers especially to possible results of the questionnaire. Phenomena like webcam covering, as analyzed by Machuletz et al. [MLB18], show the increasing privacy awareness of people. Privacy concerns may arise from social exchanges rather than intrinsic privacy concerns. Nonetheless, people act privacy preserving. More and more cameras are being installed in vehicles, and connected vehicles could enable hacking scenarios similar to those already occurring in the private computer sector [BC14]. I expect that in-vehicle cameras directed at the driver may lead to similar privacy concerns. This questionnaire and its outcome may be meaningful to participants in the way that the participant may express privacy concerns about in-vehicle cameras.

Another parameter that influences motivation is the amount of time participants spend completing the questionnaire. A large amount of time required for participation reduces the motivation to answer questionnaires [Hol16]. To keep the duration of the implementation limited, a short online questionnaire is chosen. The questionnaire should take less than ten minutes to complete. The motivation of the participants can decrease if the expected success of the survey can be low. In this case, it is a decrease in motivation because the automotive industry would be more likely to respond to the voice of the customer if customer privacy concerns would lead to a decrease in market share. In addition, driver monitoring systems are often provided by the same suppliers. Customers often have no alternative to camera-based systems if they want to use fatigue detection systems, for example. Moderate motivation might argue for a qualitative survey instead of the proposed quantitative method. The current expected target group, however, which includes almost every potential car user in Germany, is very large. A qualitative method may not achieve a large sample diversity. Another important point is the comprehensibility of the questionnaire [Hol16]. While most people know what data is recorded by cameras and know the expressiveness of an image, few people know about capacitive proximity sensors. In order to provide participants with meaningful information about capacitive proximity sensing, it is necessary to at least explain the data collected and how capacitive proximity sensing is installed. This must all be done in an understandable manner so that a direct comparison can be made between the output of capacitive proximity sensing and an associated camera view of an in-vehicle assistance system. The explanation of capacitive proximity sensing is reduced to its basic

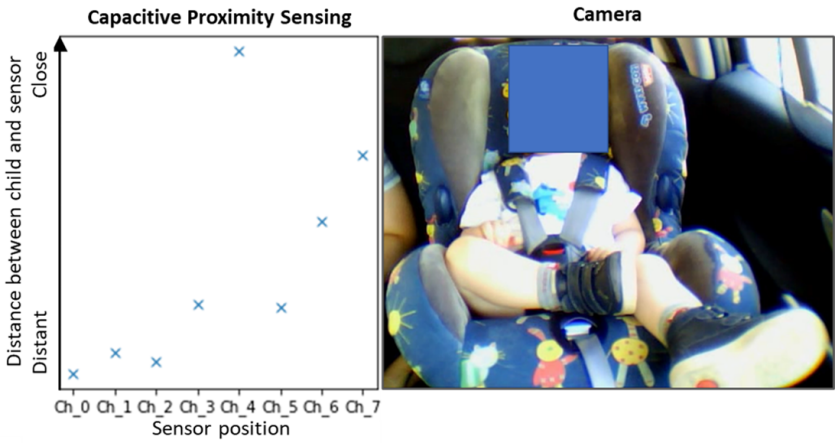



Figure 3.8.: Output of the capacitive proximity sensors (left) and camera (right) [FK20c]

characteristics. The explanation of capacitive proximity sensing is part of the introduction of the survey and is covered in Section 3.2.2.4.

#### 3.2.2.3. Questions and question types

Closed response categories are chosen for all questions. This is to ensure reliable statistical measures. Closed questions are also easier for participants to answer [May13, p. 94]. Eight questions concerning privacy follow the demographic part presented in Section 3.2.2.1. Participants can rate their privacy concerns using Likert [Lik32] scaled questions from "strongly disagree", over "disagree", "neither agree nor disagree", "agree" to "strongly agree". Likert-scaled questions are applied separately for cameras and capacitive proximity sensing. Each Likert-scaled question pair is followed by a selection question. This question allows participants to choose which system causes greater privacy concerns. This triple of questions is repeated three times. First, participants are asked without restriction. Then, the location of data processing is restricted to local and outside the car. Each triple of questions aims to test hypotheses H1 and H2 from Section 3.2.2. Participants are then asked to select the system of their choice (capacitive proximity sensors or camera). The last question of this block aims to answer the question whether people prefer capacitive proximity sensors over camera-based systems. This relates directly to hypothesis H3. Furthermore, participants are asked which system they would spend more money on, capacitive proximity sensors or camera-based systems. This question block is linked to the condition that both systems work equally well.

#### 3.2.2.4. Design of survey introduction

Motivation to complete the survey should be increased by an introduction. It is expected that many participants use vehicles [FG19]. German vehicle users are the target group. Due to the widespread availability of cameras, many participants should be aware of what data is captured by cameras. Nevertheless, only a few participants may know what data is captured by capacitive proximity sensing. Therefore, an example of capacitive proximity sensing output and an example of an image captured by a vehicle camera are added to the introduction. Both are shown in Figure 3.8. Based on Figure 3.8, it is explained that capacitive proximity sensing output is shown on the

left. To simplify the explanation, the output of capacitive proximity sensing is shown on the y-axis as "distance between child and sensor". The x-axis indicates that there are different positions of the capacitive proximity sensors. Then it is explained that the output of the capacitive proximity sensor is related to the distance between the child and the child seat. It is also explained that both systems relate to the same intent: to measure the movements of children in child seats. Since an unbiased opinion of the participant on the systems is requested, the introduction and the entire questionnaire do not provide information on privacy risks of the systems, nor on advantages or disadvantages of the systems.

#### 3.2.2.5. Pretests

A pretest is an instrument to check and improve the design of the questionnaire [Hol16, p. 24]. The pretest results aim to increase comprehensibility, decrease dropout rate, and increase significance for hypothesis testing. A pretest will be conducted with 15 subjects. Two pretest cycles will be conducted. Each participant was instructed to write comments on the questions and the structure of the questionnaire. There was no initial instruction other than informing them to write comments on understanding the questionnaire. After the initial pretest was conducted, the interviewer and pretest participants engaged in conversation. This will assess further details about the participants' comments and a general review of the comprehensibility of the questionnaire. Due to the pretest, it became obvious that initial questions like *"My privacy concerns when using capacitive proximity sensors in the car are lower compared to using cameras in the car"* (EX1), in combination with Likert scaled questions, may influence participants. Those questions are therefore changed to single selection questions. EX1 is therefore changed to: *"Select the sensor system that creates greater privacy concerns when installed in cars."*. Moreover, the answers changed as well. Participants can now choose from *"Cameras"*, *"Capacitive proximity sensors"*, *"I have great concerns. The same for both systems"* and *"I have little concerns. The same for both systems"*. It is found that subsequent refinement of questions such as EX1 can lead to significant information for the hypotheses. The refinement is implemented by asking individuals if they mind if the data is stored and processed locally or remotely.

Since this is an online survey, the target group must be extracted. It became clear that the initial question about having a driver's license would not add any information. Therefore, participants are asked if they use a car, as a passenger or driver. Additionally, demographic questions are placed at the beginning of the survey. It is expected that participants will be made aware of privacy issues during the privacy-related questions and will not want to answer the demographic questions at the end of the survey. Additionally, prior to the pretest, questionnaire participants were forced to select an answer even if they did not want to answer. This could lead to survey cancellations or randomly selected answers [May13, pp. 93–94]. Thus, the answer option *"Not specified"* is added to all questions. The dropout rate of the survey should therefore be reduced. Based on indications from the participants of the pretest, the introduction and especially the description of capacitive proximity sensing output was simplified. The measured time to complete the survey is less than ten minutes.

## 3.3. Summary

The aim of Chapter 3 is to identify an appropriate concept so that research questions RQ1, RQ2 and RQ3 can be addressed. Because of the relationship between RQ1 and RQ2, the concept for these research questions is interdependent. Specifically, the goal of the concept for RQ1 and RQ2 is to develop meaningful applications to demonstrate the importance of capacitive proximity sensing in automotive applications. In the case of RQ3, the applied concept is different. The privacy attribute for sensor systems and driver assistance devices needs to be

investigated in terms of the law and user perception. The following list shows the research questions addressed in this thesis:

- RQ1: How can we use existing vehicle structures to enhance or substitute vehicular human machine interfaces using capacitive proximity sensing?
- RQ2: How can we use existing vehicle structures to provide new ways of human computer interaction using capacitive proximity sensing?
- RQ3: Can capacitive proximity sensing contribute to the acceptance of vehicular human machine interfaces with regard to privacy concerns?

Already in the first step of the concept, RQ1 and RQ2 include the question of how in-vehicle human machine interfaces can be improved or replaced, or how new interaction possibilities can be created. In this step, existing systems, research, and statistics are examined to develop ideas for new applications that can support the vehicle user. Based on the following steps of the concept, the required capabilities will be gathered and whether these actions can be enabled with capacitive proximity sensing. This is also necessary to answer both research questions. Nevertheless, both research questions will use existing vehicle structures to limit the impact on the design and enable invisible integration. Existing vehicle structures are taken into account in Step 7 of the process. In this step, a suitable vehicle structure is selected as a carrier for capacitive proximity sensing electrodes. Regardless of whether applications are developed, consideration must be given to multiple sensor systems that could be used. A fusion of sensors could also augment existing systems. Step 8 was therefore extracted from Braun's dissertation and modified for vehicular applications. This step is necessary to select the best sensor system for the required capabilities. It should be noted that the benchmarking model used in this thesis is not necessarily best suited for all developments. It was selected to test the best sensor system for the researcher trying to help drivers or passengers of a vehicle. It may not be appropriate in the environment of a customer-driven development because the customer is not explicitly involved. In this case, another analysis tool could replace benchmarking. For example, the analysis as presented by Pugh [Pug81] includes the customers voice and can thereby help to select the best system without bias. The benchmarking process is followed by a development and an evaluation step. This part is a selection of best practices from real-world system development experiences. I do not claim that these are all processing and evaluation steps for every capacitive proximity sensing application in vehicles. Nonetheless, some parts of these two steps are critical to be promising for evaluation. On the one hand, proper labeling of the data is required to train models that can handle the nonlinear behavior of capacitive proximity sensing data (with respect to distance to objects). On the other hand, the construction and use of the vehicle structure is mandatory to prepare a test environment. In general, research question RQ1 is addressed by the concept at this stage. Nevertheless, some modifications are made to address RQ2 as well. Key paradigms for natural interaction are singled out and distributed among the concept stages. Developed applications according to this modified concept should be able to provide meaningful interaction mechanisms in vehicles.

In addition to views on the development of interaction or interface devices in vehicles, research question RQ3 aims to evaluate one particular attribute of human machine interfaces in vehicles: privacy. This concept demonstrates how existing systems can be analyzed based on government regulations. In particular, if an existing system is capable of collecting privacy-related information, this could pose a conflict with the privacy by design paradigm required by the GDPR. This approach was presented by means of an example. Furthermore, the subjective perception of vehicle users regarding privacy in vehicles needs to be determined in order to address the second part of RQ3. The design of a corresponding questionnaire was therefore shown in Chapter 3. In general, both approaches to how privacy concerns can be captured contribute to the question of how to increase the adoption of capacitive proximity sensing in vehicles. In the following chapters, the concept is applied to several applications. Applications for in-vehicle human machine interfaces are presented in Chapter 4.

# 4. Developing vehicular human machine interfaces using capacitive proximity sensing

The approach of this thesis, how to develop a capacitive proximity sensing-based vehicular human machine interface, is shown in Chapter 3.1. While the concept is applicable to a variety of possible applications in the vehicle, two applications are selected to show how this concept is applied to find evidence for research question RQ1: *How can we use existing vehicle structures to enhance or substitute vehicular human machine interfaces using capacitive proximity sensing?* Driver monitoring is considered to be possibly one of the most important monitoring systems. Even though vehicle users are increasingly supported by the vehicle systems up to automated driving, the driver is yet still in charge of controlling the vehicle. Road and the environment have still to be monitored by the driver. To ensure that the driver is capable to do so, the state of the driver concerning for example attention is observed by driver monitoring devices. To support driver monitoring by using capacitive proximity sensing, an application for driver monitoring is developed. A possible approach for the development of a driver monitoring system based on capacitive proximity sensors is shown in Section 4.1. Section 4.1 is based on *CapSeat: Capacitive Proximity Sensing for Automotive Activity Recognition* [BFMW15] and my master's thesis *Capacitive Proximity Sensing Supported Advanced Driver Assistance System* [Fra14].

When thinking about vehicular human machine interfaces, one might automatically think of stationary vehicle equipment such as the steering wheel, the seats or the pedals. Although there are devices that are only designed for use in vehicles. The focus in the area of vehicular human machine interfaces is hardly on these devices. A non-stationary vehicle structure is therefore chosen as second example to also show potentials of non-stationary structures. This passenger monitoring system is presented in Section 4.2. An ordinary child seat is used as basic vehicle structure. Section 4.2 is based on *NannyCaps – Monitoring Child Conditions and Activity in Automotive Applications Using Capacitive Proximity Sensing* [FK20a]. In Section 4.1 and Section 4.2, the previously presented concept of Chapter 3 is applied. Section 4.1 and Section 4.2 show that the concept can be applied to vehicular human machine interfaces in particular whether capacitive proximity sensing and existing vehicle structures have to be used.

## 4.1. Driver monitoring

The first application also addresses the first vehicle structure studied in this thesis. The driver's seat is used to monitor the state of the driver. On the one hand, the driver's state is monitored in terms of attention. On the other hand, the driver is assisted to adjust the seat properly. As described in research question RQ1, the advantages of capacitive proximity sensing are used to enable this human machine interface in the vehicle. The advantage of being able to measure through non-conductive material is used to invisibly integrate these sensors into an ordinary vehicle structure. Thanks to this structure and the processing of capacitive proximity sensing data, many problems caused by inattention and improperly adjusted seats are addressed. A selection of issues addressed in this project is presented in Section 4.1.1. Based on these issues and following the concept of this thesis, opportunities that provide countermeasures to these issues are presented in Section 4.1.2. Countermeasures are then linked to symptoms of the driver in Section 4.1.3. Human emissions caused by these symptoms and indications

are presented in Section 4.1.3. Whether or not these emissions are measurable is the central question in Section 4.1.5. Before feasibility can be assessed, related work and literature will be reviewed in Section 4.1.4 to determine if similar applications exist using capacitive proximity sensing. Feasibility assessment, the decision why the driver's seat was chosen and benchmarking is presented in Section 4.1.5. After the planned application is considered feasible, development of the application can start in Section 4.1.6. Processing algorithms, a sensor topology, and a mockup with a real car seat to enable measurement of human emissions so that a driver monitoring system can be supported are shown. The system is evaluated in Section 4.1.7.

### 4.1.1. Existing systems and their issues

According to McGuckin et al. [MF18, p. 54], an U.S. worker spent more than four and a half hours per week commuting in 2017, on average. This number actually increased by half an hour compared to 2009. To be precise, people spend an average of 58.6 minutes per day as the driver or passenger of a vehicle. Drivers therefore have a great responsibility to themselves, their passengers and other road users. Advanced driver assistance systems are being developed to help drivers drive safely. That said, according to the IIHS [Ins19], 37,473 people died in car crashes in 2017 (2018: 36,560), involving 53,128 vehicles (2018: 51,872). In 2018, 5% of drivers were distracted in these accidents. This is only the estimated number, while the unreported number could be higher and more accidents could be caused by distraction. 61% of these accidents or 1,654 accidents were caused by daydreaming. Inattention due to distraction or drowsiness is thus a cause of fatal accidents. Problems with drowsy driving in 2015 are presented by NHTSA [NHT17]. In their report, they cite a figure of 2.3% of all fatal crashes in the United States caused by drowsy driving. Again, the number of unreported cases may be much higher because drivers do not want to admit to drowsy driving. Following these statistics, a system that detects drowsy driving is needed so that drivers can be warned.

Another issue is being addressed in this project. The correct seat adjustment is crucial for a safe ride. Following Dissanaike et al. [DKM*08], an improperly adjusted backrest can lead to serious injuries. In their study, car crashes in the United States between 1995 and 2005 are examined. Based on their study, improperly adjusted backrests can lead to severe thoracoabdominal and spinal injuries. This leads to high mortality. Farmer et al. [FWL03] show that an improper setup of the head restraint can lead to injuries due to neck whiplash. It is also important that the seat position ensures a correct knee angle so that the driver can apply full force to the brake pedal in the event of an emergency stop.

Parts of these issues are already addressed in the literature. A system for measuring anthropometric characteristics of the driver is provided by Lorenz [Lor11]. Through a variety of sensors, the seat height and the posture of the driver can be detected. Pressure mats are used, for example. The headrest is then automatically adjusted. Pressure mats are also used by Riener [Rie10]. In his system, these mats are placed on the driver's seat so that drivers can be identified. From the dynamic transition of the pressure distribution measured by the pressure mat, activities of the drivers can also be distinguished. The issue here is that these sensors require contact between the driver and the seat. Since out-of-position of the head takes place in free air, it cannot be detected with these sensors. Besides anthropometric characteristics, Li et al. [LWC*14] use a depth camera to rate the tiredness and attention of the driver. Symptoms such as gazing or eye closure are detected by the camera. Nevertheless, cameras can capture information relevant to data protection. One issue that should therefore be avoided is the collection of personal data such as facial images.

### 4.1.2. Opportunities

There are several opportunities that serve as countermeasures to the issues identified in Section 4.1.1. Since fatigue and inattention can lead to fatal accidents, the system should detect driver symptoms of inattention and fatigue. The correct seat position is also crucial for safe driving. Therefore, one opportunity is assisted seat adjustment, so that the driver or even an automated system can adjust the driver's seat to a proper and safe position. Related to seat adjustment is driver posture detection. To prevent airbag out-of-position or whiplash, one opportunity is to measure the driver's current posture so that an assistance system can adjust the appropriate parameters. For example, the airbag could be deactivated when the driver intersects with the deployment area.

### 4.1.3. Symptoms, indications and human emissions

Several countermeasures for the issues presented in Section 4.1.1 are named in Section 4.1.2. Fatigue and attention measurement in particular should be supported and seat adjustment monitored. In addition, incorrect postures should be avoided. First, symptoms of driver drowsiness are examined. Possible symptoms are named by Watson et al. [WMC*15]. Whether the driver is tired, frequent yawning or nodding off can occur. Heart rate changes are named by Fujiwara et al. [FAK*19] as a further symptom of drowsiness. Further symptoms like yawning or gazing are named by Klösch et al. [KHZ20, p. 13,65]. In addition, erratic steering maneuvers can occur as shown by Dingus et al. [DHW87]. In particular, Dingus et al. specify a critical steering wheel velocity to be periodically greater than 150°/s. Gazing is also named as symptom for tiredness by Shiferaw et al. [SDW*18]. Gazing is indicated by the driver looking at a particular point for an extended period of time. So, the human emissions are the eye movement and the head movement. While the driver is nodding off, the head movement is also the significant human emission. The next symptom considered in this paper is yawning. During this event, the usual breathing is interrupted. Since the chest is moved up and down, the human emission considered for this symptom is the upper body movement. The steering movement results in movement of the arms. Therefore, it is expected that the movement of the arms is related to the steering wheel speed and frequency.

Seat adjustment involves looking at the position of the head relative to the headrest to make a decision as to whether the headrest is properly adjusted. The backrest adjustment depends on the angles of the arms. Arm positions are therefore considered as the human emission of interest. The seat adjustment further depends on the leg position of the driver. Positions of the legs relative to the seat are considered as human emission. In addition to the posture for seat adjustment, the posture of the driver while driving must also be monitored to distinguish between incorrect posture, correct posture, and the risk of whiplash. All of these positions relate to the driver's head posture. The position of the upper body also plays a role, as the driver may lean forward.

### 4.1.4. Physical characteristics and related work

Various human emissions are identified in Section 4.1.3, whose detection can help enable countermeasures for problems arising from existing systems or statistics of causes of accidents or injuries. We now establish a link between the emissions and capacitive proximity sensors. Changes in the electric field caused by moving objects can be detected using the capacitive proximity sensors, as already shown in Section 2.1. Human emissions related to the driver's movements can thus be measured. If a sensor topology can be designed that is close enough to the associated units of the human body, the position and motion of the head, torso, arms, and legs should be measurable. This allows the detection of almost all human emissions except eye movements, which are mentioned in Section 4.1.3. Since the eyeball moves within the head, it is assumed that position changes of the eyeball cannot be measured with capacitive proximity sensing. No related work has been found that indicates eye position detection based on capacitive proximity sensing. Nevertheless, there is related work in which capacitive

proximity sensing is used to detect users' body postures. For example, in a publication of Braun et al. [BFW15], a regular office chair is equipped with capacitive proximity sensors. This enables them to detect the user's activity and posture on the chair. Arm positions are included in this posture detection. Breathing rate is also measured in this project. So, the basis of the required human emissions is covered with this modified office furniture. The breathing frequency detection in particular suggests that yawning could also be detected. There are further publications that give indications whether the capacitive proximity sensing is suitable to measure the required human emissions. Rus et al. [RGPK14] equip sheets of a regular bed to detect lying postures of the user. Cheng et al. [CAL10] attach capacitive proximity sensors to different body parts so that swallowing, speaking and sighing can be detected. The position of the arm is even monitored in vehicles using capacitive proximity sensing. In a publication of Braun et al. [BNS*14], the driver's armrest in the vehicle is equipped with capacitive proximity sensing so that arm positions can be distinguished and finger gestures recognized. Based on these publications and the general characteristics of capacitive proximity sensing, a foundation is formed for Section 4.1.5, where a judgment is made on the feasibility of this project.

### 4.1.5. Feasibility, vehicle structure and benchmarking

Based on related work and the physical properties of capacitive proximity sensing, most of the features to be developed in this project are considered feasible. However, the detection of eye position is an emission that may not be detectable with capacitive proximity sensing. For the remaining entities, head position, arm position, upper body position, leg position, and thoracic motion, vehicle structures that can be equipped with capacitive proximity sensing must be found. Regarding the head position, the interior roof above the driver's head could be an option. Another option could be the headrest, since it is also close to the head. Arm position, and thus arm movement related to steering movements, could be measured with sensing electrodes in the side cushion of the backrest or in the steering wheel. Leg position could be derived with sensors in the seat cushion and the vehicle leg compartment. Further, thoracic motion is close to the backrest of the vehicle. Many of these vehicle structures are integrated into the driver's seat. Therefore, this project focuses on the modification of the seat. Nonetheless, structures such as the leg compartment and steering wheel are also addressed in this thesis. An equipped leg compartment and derived features are discussed in Section 5.3. A capacitive proximity sensing equipped steering wheel is shown in Section 5.1 and Section 5.2.

Now that the vehicle structures for mounting the capacitive proximity sensors have been defined, the combinations of structure and sensor can be compared with other sensor systems in a benchmarking process. Before the benchmarking can be calculated, the weights for the application must be defined. Each human emission to be evaluated can have different weights. For example, the required detection range for yawn detection is considered close to zero, since the contact between the seat and the thorax could already provide breath monitoring, while head position detection requires a detection range of about 30 cm. Nevertheless, the goal of this project is to develop a complete application for all features. The application weights are therefore estimated according to the most constraining value. The resolution weight is set to a medium value for a resolution of 5 mm. This is derived from the yawn detection feature. The update rate is set to a mean value of 20 Hz. Real-time processing should be sufficient for events such as nodding detection. Furthermore, the detection range weighting is set to low with a range of up to 30 cm. 30 cm should be sufficient for detecting position deviations, larger detection ranges do not contribute to the feature. Since almost the entire body of the driver is monitored, the unobtrusiveness is set to high. Since this project is in the prototyping phase, the complexity of processing and calibration is set to medium weight. Next, the weighting for robustness is set to a high value, as the detection of position deviations should be robust. Likewise, the disturbance frequency is set to a high value for the same reason. The last weighting is for unique limitations. If the sensor is able to meet the previous requirements, there are no further limitations. Therefore, this metric is neglected.

| Feature | Camera | Capacitive proximity sensing | Ultrasonic sensor |
|---|---|---|---|
| Resolution | ++ (320x240 px) | o (5-15mm) | ++ (0.025mm) |
| Update Rate | ++ (25-50 Hz) | + (25Hz) | - (12 Hz) |
| Detection Range | ++ (>1m) | o (>30cm) | ++ (65-600mm) |
| Unobtrusiveness | - | + | - |
| Processing Complexity | + | o | o |
| Robustness | o | o | o |
| Disturbance Frequency | - | o | o |
| Calibration Complexity | o | o | ++ |

Table 4.1.: Overview of sensor characteristics

Then ratings for sensors can be defined. So, a set of sensors is needed that can enable the functions. Yawn detection, seat and backrest adjustment could be facilitated by using pressure sensors. Nevertheless, pressure sensors are not considered because not all features can be covered. A camera (e.g.: [Ope20b]) could enable almost every feature. It could be integrated into the vehicle's interior roof and leg compartment. In addition, an array of ultrasonic sensors could enable the functions. In this case, an exemplary sensor of Microsonic [Mic20] is used. The ultrasonic sensors could be installed in the steering wheel, interior roof, footwell, door, and center console. Based on the characteristics of the sensors, metrics can be defined for benchmarking. The required characteristics and ratings of the sensors are shown in Table 4.1. Neither ultrasonic sensors nor cameras can be installed invisibly in the vehicle interior. Facial images could also be captured by cameras. Rating for unobtrusiveness is set low. The rating for ultrasonic sensors is also set low. While they may not compromise privacy, they must be visibly integrated at various locations in the vehicle so that all human emissions can be monitored. The processing complexity of the ultrasonic sensor and capacitive proximity sensors is set to medium. It is expected that the output of both sensors will be processed using estimators. Processing complexity for the camera is rated good. According to the manufacturer, the camera is already capable of processing face recognition on the chip. Nevertheless, the disturbance frequency for the camera is rated as low. Changing light conditions and clothing will likely interfere with the measurement. Capacitive proximity sensors and ultrasonic sensor do not have these limitations. However, clothing could also disable breath detection for ultrasonic sensors. Capacitive proximity sensors could be disturbed by moisture. The benchmarking scores for the system are therefore 0.57 for the camera, 0.58 for the capacitive proximity sensors, and 0.55 for the ultrasonic sensors. So, the capacitive proximity sensors are best suited for this application. Nonetheless, this is a subjective evaluation. If one were to neglect a metric such as unobtrusiveness, the camera sensors would win the benchmarking. Also, many evaluations are based on estimates.

### 4.1.6. Develop

We have identified the driver's seat as a suitable base for the use of capacitive proximity sensors. For this reason, the driver's seat must be equipped with capacitive proximity sensors so that the expected features can be realized. The concept for the sensing electrodes is shown on the left in Figure 4.1. Each human emission to be evaluated is addressed by different sensor positions. Electrodes are inserted in the headrest to measure the position of the head. Sensors are built into the backrest to measure the distance to the arms and thus the steering movements, and sensing electrodes are built into the sitting area to allow seat adjustment. A total of 16 sensing electrodes are used. As shown in the middle of Figure 4.1, the sensor concept is implemented into an ordinary vehicle seat. The sensors are then covered by a seat cover. The finished seat prototype is installed in a demonstrator. The


Figure 4.1.: Concept and implementation of sensing topology [BFMW15, Fra14]

demonstrator is shown on the right side of Figure 4.1. Two OpenCapSense toolkits [GPBB*13] are installed in the mockup. The data for each sensing electrode is transmitted at a sampling rate of 25 Hz. To enable testing and data acquisition for the seat adjustment functions, the headrest, the backrest and the longitudinal distance between the seat and the pedal as well as the pedal inclination are adjustable. In the further processing models, the backrest sensors are prefixed with B1, which stands for board one, and the seat sensors are prefixed with B0.

Now that data on the distance of the driver's extremities can be provided, suitable concepts for data processing must be found. For attention monitoring, features for gaze detection, steering speed monitoring, yawn detection and nod detection need to be identified. Features for seat adjustment for headrest, backrest and seat length adjustment must also be found. Out-of-Position detection and occupancy recognition are to be set up. Occupancy detection is the first considered feature of the application. It serves as the basis for further processing, which is active only when the seat is occupied. To detect occupancy, the data from all sensors are MinMax scaled. Then the data is fed into a linear support vector machine. Linear separability is expected. There are two classes: If a subject is sitting on the seat, it is labeled as occupied. If the subject is not seated, the seat is labeled as empty. The occupancy detection system should not detect the class occupied if the subject is not sitting on the seat. Therefore, data such as a hand on the seat should be used to evaluate the concept.

After occupancy, the driver usually adjusts the seat. The assisted seat adjustment is the next considered feature of the project. The first feature is the headrest adjustment. The relative difference between the driver's height and the position of the headrest should lead to an assessment of whether the headrest is correctly adjusted. To distinguish between a correct headrest adjustment and a too high (>5cm) or too low (<5cm) position of the headrest, a support vector machine classifier is used. The feature vector for this model is composed of the MinMax normalized data from the backrest and headrest sensors. The backrest sensors are also included because these data are expected to contain information about the driver's torso length that is related to a person's height. In advance of the MinMax normalization, a median filter with a kernel size of three is applied. Then, the system can provide feedback on the adjustment direction of the headrest. In addition to the headrest, the seat longitudinal adjustment shall also be supported. In particular, the adjustment of the seat shall lead to a comfortable and ergonomic pedal operation. From multiple optimum knee angles as presented in a literature review of Schmidt et al. [SAF*14], a knee angle between 110° and 120° is considered best in this project. A knee angle of 115° is therefore selected as a class for a classifier. An angle that is too large is considered as a class as well as an angle that is too small. The feature vector for the classifier consists of the processed data from the seat sensors. Each channel value of a sample is divided by the sum of all channels for that sample. The result thus represents the ratio of the measured sensor values. In addition, the raw sensor value minus the minimum sensor value is used. These processed sensor values contribute to a feature vector for a random forest classifier with 100 estimators.

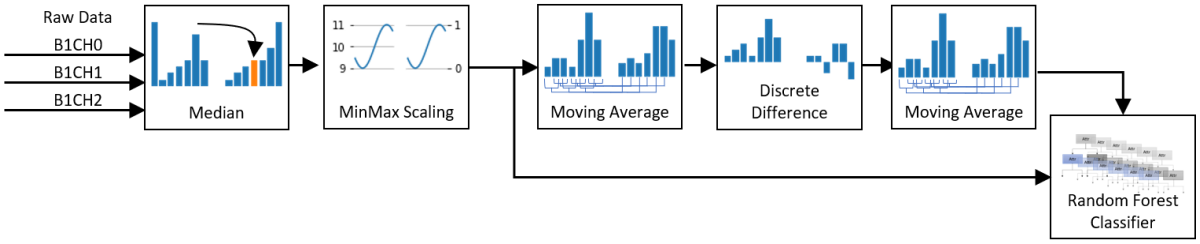



Figure 4.2.: Gaze recognition data flow

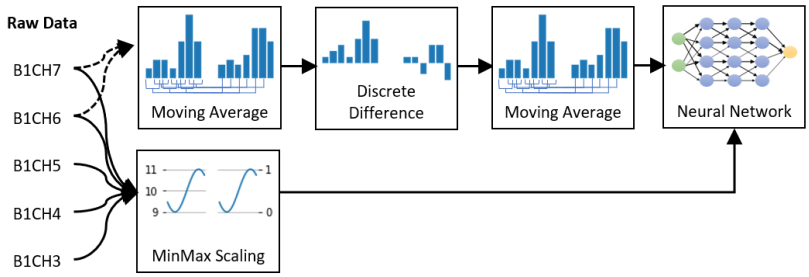



Figure 4.3.: Steering velocity monitoring data flow

The raw sensor value minus the minimum sensor value is used because these values should contain information about the height and weight of the subject.

After the seat is adjusted, the driver usually starts driving. Therefore, attention monitoring becomes one of the essential functions for the application. One symptom of drowsy driving is gazing. Gazing results in few head movements. This is taken into account during data processing. The data processing flow is shown in Figure 4.2. As shown in Figure 4.2, the sensors close to the head are included for gaze recognition. Specifically, the sensors of the headrest are used (B1CH0, B1CH1, B1CH2). First, all sensors are filtered using a median filter with a kernel size of three. Then, MinMax scaling is applied to all three channels. The result of this operation is directly added to the feature vector for the subsequent classifier model. In addition, a moving average filter with a window size of five is applied to the scaled data. This is done to prepare the data for discrete difference processing. The output of this processing is smoothed using a moving average filter with a window size of five. The result of this process is also added to the feature vector for the classifier. Gazing is a process that is established over time. Therefore, the data is divided into time windows of 0.2 seconds.

The next feature considered for attention monitoring is steering wheel speed. The steering movement leads to the movement of at least the arms and the upper body. In order to measure the steering speed only with capacitive proximity sensors, an algorithm is developed to record these movements. As shown in Figure 4.3, the back rest sensors are used. The preprocessing is split into two parts. In part one, channels B1CH6 and B1CH7 are processed. These channels relate to the seat side cushion close to the driver arms. It should therefore be possible to detect the arm movement with these sensors. Sensor values of these two channels are processed by using a moving average filter. The window size of the filter is five samples. Afterwards, the discrete difference is computed. The same moving average filter is applied to the discrete difference data again. Since the dependence

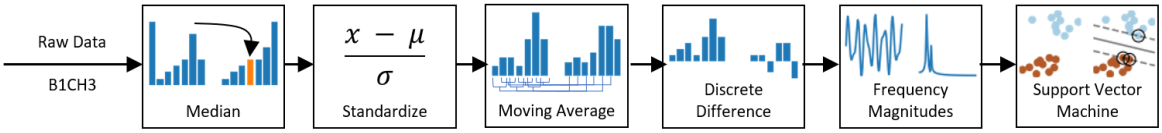



Figure 4.4.: Yawn recognition data flow

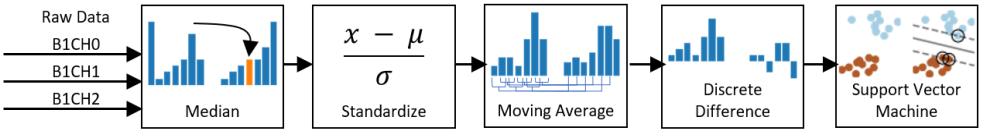



Figure 4.5.: Nod recognition data flow

between sensors and arm distance is non-linear, sensor values which should indicate the upper body and arm position are included into the preprocessing. Data of all considered channels are therefore processed using MinMax normalization ($y = \frac{x - x_{min}}{x_{max} - x_{min}}$). The resulting data of both preprocessing parts is concatenated. Since there can be a time delay between the arm movement and the steering wheel movement, the resulting data is divided into windows of 0.2 s. Using those chunks, a feed forward network is trained. The network consists of one hidden layer with 60 neurons. The activation function is Rectified Linear Unit. Since a hint for tiredness is the actual steering speed, the dataset can be separated into two classes. In particular, the data is split into data with an absolute steering velocity less than 150°/s and greater than or equal to 150°/s.

Gazing and suspicious steering are one hint for tiredness or inattention. An additional hint is frequent yawning. During natural breathing, yawning is believed to disrupt normal breathing and will therefore change the frequency spectrum. Breathing should be best visible in the upper back area. The lungs fill with air and the chest rises and falls. This chest movement should be measurable. The upper back sensor (B1CH3) is therefore selected as basis for a classification model. Before the frequency spectrum can be computed, the measured data of B1CH3 is filtered using a median filter with a kernel size of three. Afterwards, the resulting data is standardized ($Z = \frac{x - \mu}{\sigma}$). Additionally, a moving average window is applied to the data. The window size is 10 samples (0.4 seconds). Afterwards, the first discrete difference for each element is computed. Using this data, another moving average filter with a window size of 10 samples is applied to smooth the data. The resulting data are windowed into chunks of 200 samples (eight seconds). This is an empirical value selected due to the yawn durations during evaluation. The amplitudes of the frequency spectrum for each block are calculated. The final feature vector is comprised of the first 20 entries of the magnitudes. A range from zero to 2.5Hz is included. The regular respiratory rate of an adult is about 20 breaths per minute. This equals ≈0.33Hz. The final feature vector is fed into a support vector machine classifier. The whole process is visualized in Figure 4.4

When someone nods off at the wheel, it is a strong indication of fatigue. A nodding off is considered to be a head movement in which the head looks straight ahead and suddenly drops, causing the driver's view to move downward. Head movement is therefore considered the main indicator. So, the sensors of the headrest (B1CH0, B1CH1, B1CH2) are selected as the basic processing input for a classification model. In particular, the discrete difference of the sensors is used. In advance, the measurement data of each channel is filtered using a median filter with a kernel size of three. The resulting data is afterwards standardized ($Z = \frac{x - \mu}{\sigma}$). Additionally, a moving average window is applied to the data. The window size is 10 samples (0.4 seconds). Then, the first discrete

difference is calculated for each element. The resulting data is windowed into chunks of 38 samples (≈1.5 seconds). This is an empirical value selected due to the nod durations during evaluation. This data window is used as feature vector for a support vector machine classifier. The whole process is visualized in Figure 4.5.

In addition to occupancy, seat adjustment and fatigue, a fourth characteristic is examined. In particular, dangerous driver postures are to be identified with regard to the driver's head position. If the driver's head is too close to the steering wheel or too far from the headrest, this indicates a dangerous position in the event of an accident. If the head is too close to the steering wheel, it may overlap with the deployment area of the airbag (class: Airbag). If the head is too far from the headrest, the driver may suffer neck whiplash in the event of an accident (class: Whiplash). Proper position is when the distance between the head and the headrest is less than five centimeters (Class: Proper). The position of the head refers to the sensor values of the backrest and headrest. Therefore, the sensor values of the backrest are used for processing. Nevertheless, seating sensors may contain further information about the subject's position. These sensors are also included in the processing. In particular, all sensor values are MinMax scaled. A median filter with kernel size three is also applied to the raw data. Using these 16 channels, a support vector machine classifier is used to distinguish between the following classes: Whiplash, Proper, and Airbag.

Data processing is now defined for all features and a mockup is built and ready to collect data for capacitive proximity sensing. The acquired data, however, is not yet labeled. To prepare for analysis, a suitable data labeling procedure is defined. Markers are placed on the wall in front of the simulator for gaze detection. Each marker is placed in an angle of ≈45° relative to the straight line of sight. In addition, a marker is placed in the straight line of sight. The labels are thus gazing down, left, right, straight ahead and up. Data is also captured to simulate normal driving without gazing. The steering wheel angular rate is recorded with a gyroscope attached to the steering wheel. Subjects therefore slowly increase the steering speed to acquire data at steering speeds greater than and less than 150°/s. To capture nodding and yawning, subjects are instructed to perform the respective motion. In addition, the timestamps of the start and stop of the events are recorded. In the out-of-position measurement, the distance between the head and the headrest is measured. In this case, subjects are instructed to move their head in the specific ranges of the out-of-position classes. In the case of seat adjustment, data are collected at different correct and incorrect positions of the subjects. Thus, each data set consists of only one class of seating positions. Data collection and subsequent data labeling is embedded in an application so that participants in a study can be instructed. Icons are used to indicate what the subject should perform when data of a particular feature is collected. Now that a prototype has been built, the concepts for data processing have been designed, and the data can be labeled, the system is ready for evaluation in Section 4.1.7.

### 4.1.7. Evaluate

Concepts for seat adjustment, out-of-position detection and attention monitoring are designed in Section 4.1.6. Additionally, a mockup with the implemented sensor topology is built. The system is ready for a study with subjects. We will now discuss the outcome of this study and the evaluation. The demographic data of the subjects are presented first. Then the collected data and the evaluation for each characteristic will be presented. The study is conducted with six participants. Two of these subjects are female and four are male. The average age of the subjects is 27 years old. The weight of the subjects ranges from 64 to 100 kg and the height of the subjects ranges from 168 to 195 cm. Three of the subjects own a car, and five have a driver's license. In addition to these general questions, subjects are asked if they are familiar with driver assistance systems and capacitive proximity sensing. One subject has a lot of experience with driver assistance systems and all subjects are familiar with capacitive proximity sensing. In addition, subjects are asked questions about the system after they participate in the study. They could assign points from one to eleven, where eleven represents strong agreement. The result is that subjects agree that the system can support driver assistance systems. Subjects also agree that they would use

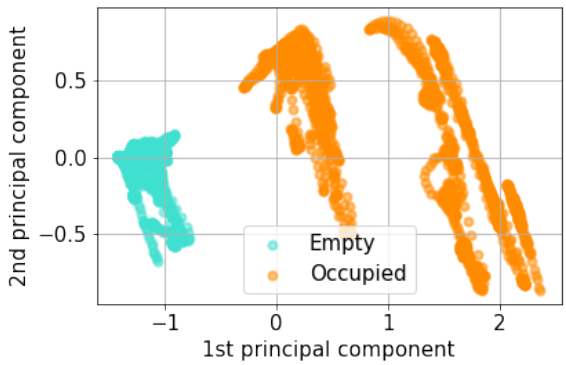



Figure 4.6.: Principal component analysis (PCA) on occupancy recognition dataset

the system if their car was equipped with it. We now go through the evaluation of the different functions. The first function is occupancy recognition.

A total of 4,783 samples (about 3 minutes and eleven seconds, Empty: 2,389, Occupied: 2,394) of data are collected at different occupancy conditions with six subjects. In particular, the empty class consists of samples without a subject and when the subject only touches the seat or puts a hand on the seat. The class occupied indicates that the subject is sitting on the seat. To visualize the dataset, a principal component analysis (PCA) on the complete dataset (as shown in Figure 4.6) is processed. Using the first two principal components, the data looks linearly separable. A support vector machine classifier is then used to distinguish between the three classes. It consists of a linear kernel. First, the whole dataset is randomly divided into 70% training data and 30% test data. 3,348 samples are used for training and 1,435 samples are used for testing. As shown in Figure 4.7, the prediction is perfect. A leave-one-out evaluation is performed. In this case, one model is trained per subject. One subject is used as test data, while the remaining data of subjects are used as training data. Then, the results of the evaluation metrics vary from subject to subject. The prediction remains perfect for subjects B, C, D, E, and F. In contrast to the data for these subjects, the prediction for Subject A shows 39 false positives. As a result, the true-positive rate drops to 0.96 (P: 870, TP: 831). The mean true-positive rate for the classifier in the leave-one-out evaluation is 0.98 and the true-negative rate is 1. The F1 score is 0.99 and the mean accuracy is about 1 (P: 2,394, TP: 2,355, N: 2,389, TN: 2,389).

After occupancy recognition has been performed, seat adjustment is the next feature to be evaluated. One feature of seat adjustment is the adjustment of headrest position. A total of 7,743 samples (about 5.2 minutes) of data with different headrest positions are collected with six subjects. The headrest is adjusted to a proper position, a too high position, and a too low position. The collected data for Subject A are shown in Figure 4.8. All diagrams in this figure refer to channel B1CH0, which is the upper headrest sensor. The data looks exclusive for each class. A principal component analysis on the complete dataset (as shown in Figure 4.9) shows that the data cannot be split linearly based on the data from one channel. The data points show multiple concentration clusters for each class. Nevertheless, these clusters overlap. A support vector machine classifier is then used to distinguish between the three classes. First, the whole dataset is divided into 70% training and 30% test data. 5,420 samples are used for training and 2,323 samples for testing. As shown in Figure 4.10, the prediction is perfect. Although there is no error when the complete data set is used, a leave-one-out evaluation is performed. In this case, one model is trained per subject. One subject is used as test data, while the remaining subject data

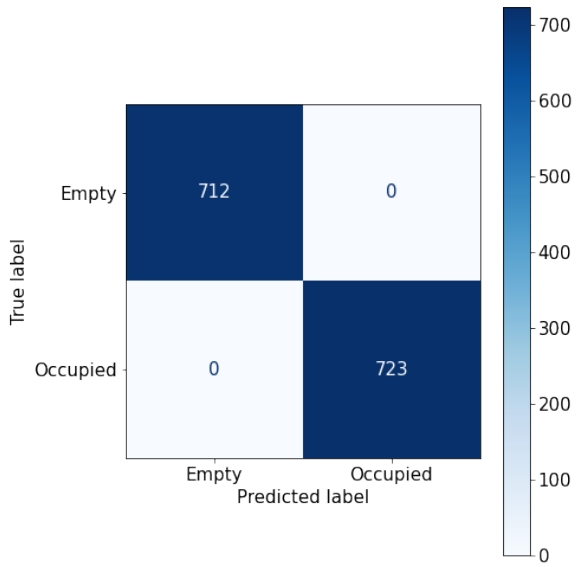



Figure 4.7.: Occupancy recognition classifier confusion matrix

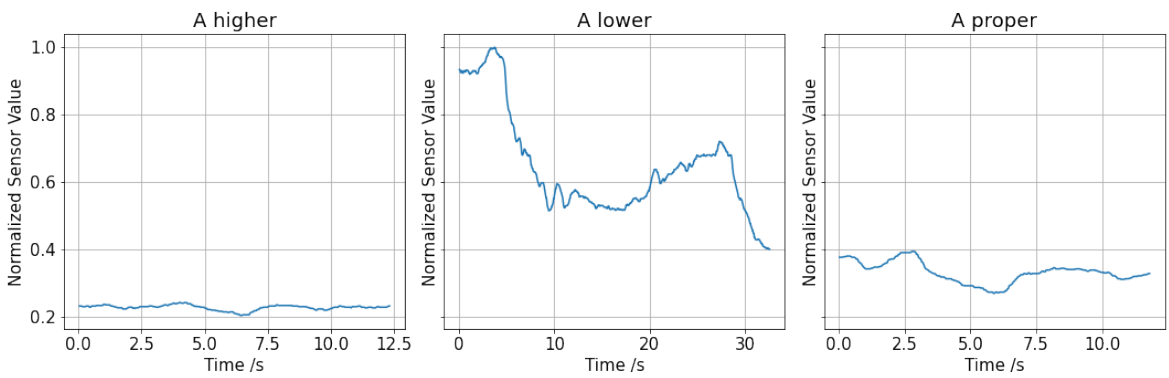



Figure 4.8.: Collected head restraint position samples for Subject A

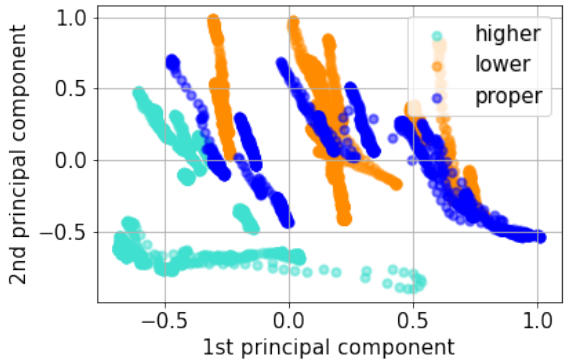



Figure 4.9.: Principal component analysis (PCA) on head restraint dataset

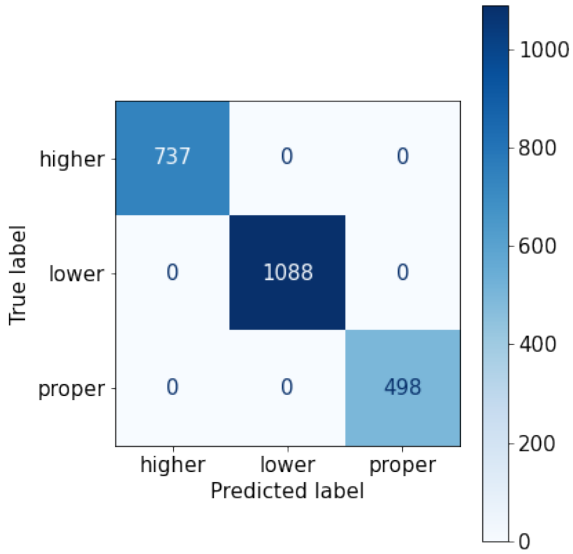



Figure 4.10.: Head restraint classifier confusion matrix

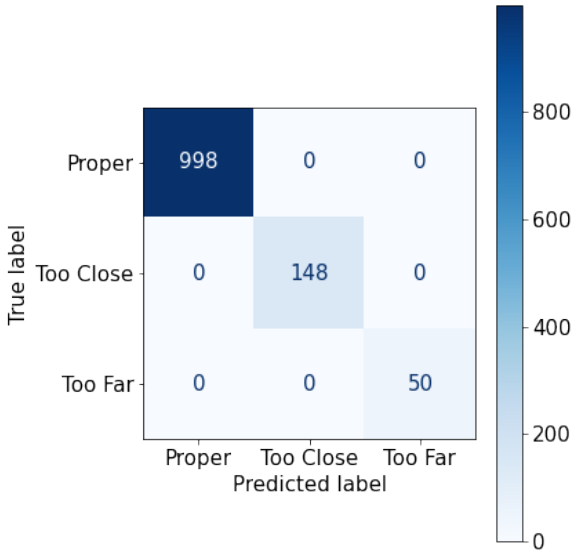



Figure 4.11.: Assisted seat adjustment classifier confusion matrix

is used as training data. Then, the accuracy varies from subject to subject (A: 0.75, B: 0.99, C: 0.74, D: 0.72, E: 1.0, F: 0.97). The mean true-positive rate for the classifier is 0.81 and the true-negative rate is 0.93. The F1 score is equal to 0.82.

The next feature considered is seat longitudinal adjustment. Using the data from the six test subjects, the feature of assisted seat adjustment is evaluated. During data collection, the longitudinal seat is adjusted to different positions. In addition, a correct adjustment is measured at a knee angle of 115°. Based on the correlation between the position at the correct knee angle and the measured longitudinal position, the classes are defined as follows: Proper - longitudinal position matches the knee angle of 115°, Too Far - position is greater than the proper position, and Too Close - position is less than the proper position. A total of 3,984 samples are collected. The data is divided into 70% training data and 30% test data. The training set consists of 2,788 samples. The test set consists of 1,196 samples. The data set is unbalanced. 2,303 samples belong to the "Too Far" class, 162 samples belong to the "Too Close" class, and 323 samples belong to the " Proper" class. Due to this imbalance, the class weights of the classifier, a random forest classifier, are adjusted. The classifier has managed to provide a perfect prediction for the test set. The predictions are shown in Figure 4.11. A leave-one-participant-out evaluation is furthermore conducted. In this case, the results are worse:

- Subject A: TPR 0.41, TNR 0.74 (Does not predict "Too Close")
- Subject B: TPR 0.74, TNR 0.75
- Subject C: TPR 0.5, TNR 0.5 (predicts only "Too Far")
- Subject D: TPR 0.59, TNR 0.88 (Does not predict "Too Close")
- Subject E: TPR 1, TNR 1
- Subject F: TPR 0.5, TNR 0.5 (Does not predict "Proper")

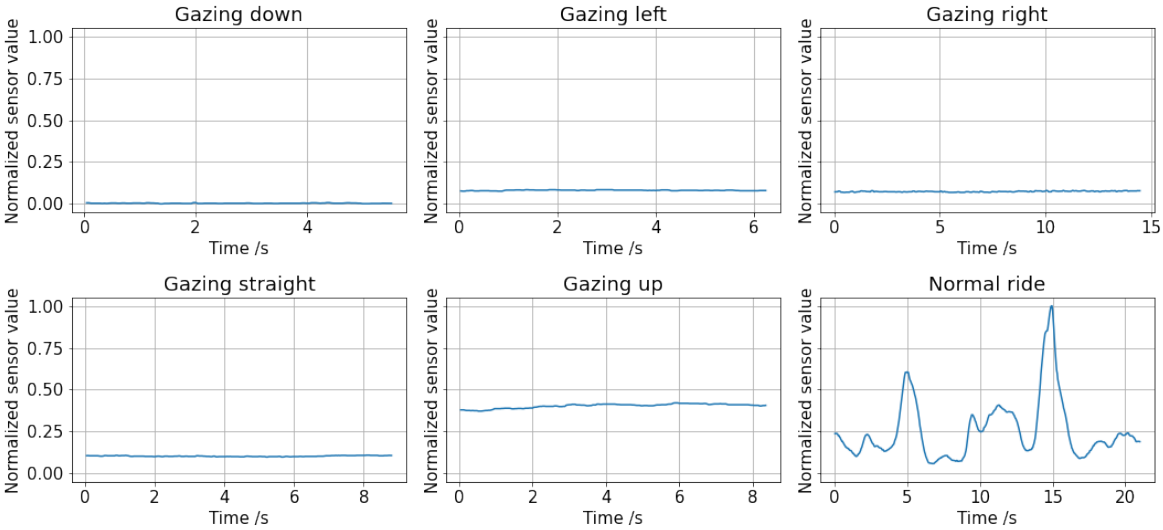



Figure 4.12.: Subject A gazing in different directions and during a normal ride

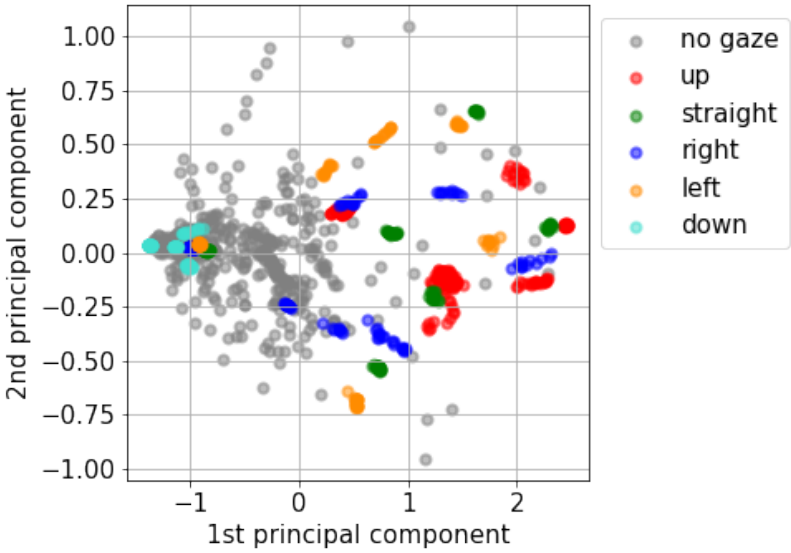



Figure 4.13.: Principal component analysis (PCA) on gaze dataset

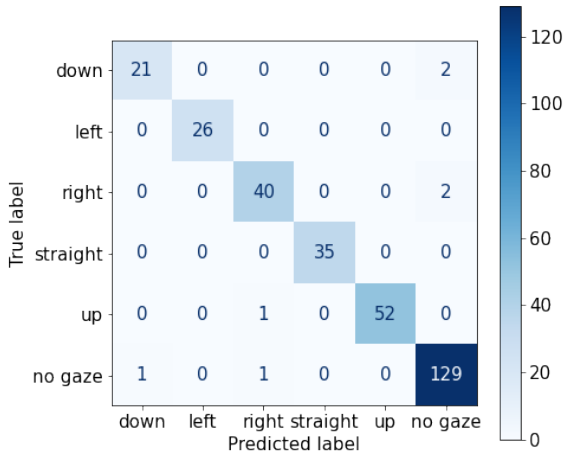



Figure 4.14.: Confusion matrix of gaze classifier

After the seat is properly adjusted, attention measurement models can be evaluated. The first symptom considered is gaze recognition. An example of recorded gaze data for Subject A is shown in Figure 4.12. The sensor data of channel B1CH1 are shown. While the sensor data remains stable during the gaze, the data changes frequently during normal driving. The collected data is processed according to Section 4.1.6. The complete data set consists of 1,031 samples with a window size of 0.2 seconds. 400 of these samples belong to data where the subject is not gazing. Two principal components of a principal component analysis of the data set are shown in Figure 4.13. The data of the class gazing down is almost hidden under the data of the class with no gaze. The remaining classes appear to have multiple locations with concentrated values. The dataset is then randomly split into 70% training and 30% test data. 721 samples are used to train the random forest classifier (100 estimators). Then, the trained classifier is tested with 310 samples. A mean accuracy of 99.2% is achieved. The individual classification values are shown in Figure 4.14. The mean true positive rate is 0.97 and the mean true negative rate is 0.99. The mean F1-Score is 0.98.

In addition to gaze detection, a suspicious steering movement is an indication of fatigue. Figure 4.15 shows an example of captured steering data. Both the data from the angular rate sensor, and the data from the capacitive proximity sensor near the right arm, were normalized by dividing the data by the absolute maximum. The data shown from B1CH7 has already been processed as described in Figure 4.3. The coefficient of determination ($R^2$) for the processed channel B1CH7 compared to the acceleration is 0.79 for Subject A, 0.62 for Subject b, 0.3 for Subject C, 0.69 for Subject D, 0.83 for Subject E and 0.75 for Subject F. The complete dataset consists of 1,824 samples. Furthermore, this dataset is divided into a training dataset and a test dataset for the neural network regression model. The ratio is 70% training data and 30% test data. The exact number of samples in the training set is 1,276 and the test set consists of 548 samples. The trained regression model is applied to the test data. A coefficient of determination of 0.91 is the result of the test. The same data set is used to train a support vector machine classifier. In this case, another class label is added to the data set. If the subject steers at a steering speed greater than 150°/s, this is placed in class one. The rest of the data remains in class zero. With this binary classification problem, a principal component analysis can be calculated. The dimensions are reduced to two principal components and plotted in Figure 4.16. Data with a steering velocity below 150°/s is centered around

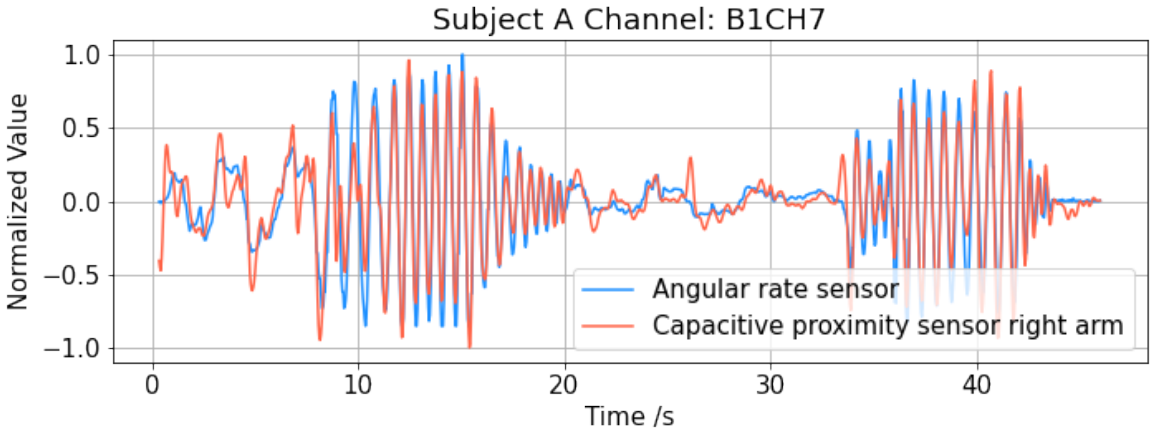



Figure 4.15.: Exemplary angular rate and capacitive proximity sensing output of the right arm sensor

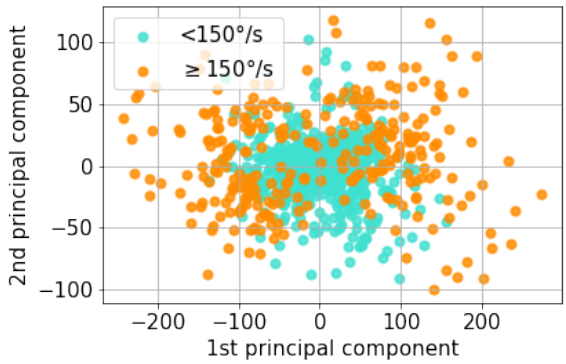



Figure 4.16.: Principal component analysis (PCA) on steering dataset

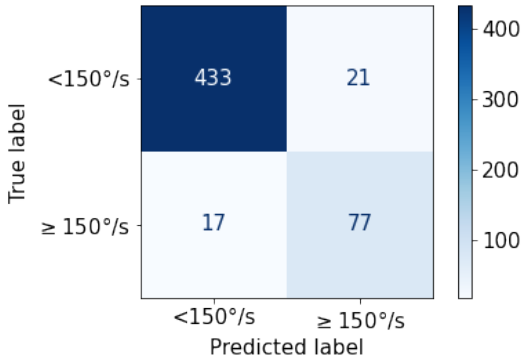



Figure 4.17.: Steering classifier confusion matrix

| Test Subject | TPR | TNR | F1-Score |
|---|---|---|---|
| A | 0.5 | 0.88 | 0.57 |
| B | 0.8 | 0.62 | 0.67 |
| C | 0.8 | 0.83 | 0.8 |
| D | 1.0 | 1.0 | 1.0 |
| E | 1.0 | 1.0 | 1.0 |
| F | 1.0 | 1.0 | 1.0 |

Table 4.2.: Yawn recognition leave-one-participant-out results

zero. Figure 4.17 shows the result of the support vector machine model test. The model is trained with 1,086 samples of $< 150°/s$ samples and 190 $\geq 150°/s$ samples. 454 samples of $< 150°/s$ samples and 94 $\geq 150°/s$ samples are used for testing the model. The number of true positives is 77 and the number of true negatives is 433. The true positive rate is 0.82 and the true negative rate is 0.95. The F1-score is 0.8.

The next considered inattentiveness symptom is yawning. The collected data for yawn recognition is shown in Figure 4.18. The figure shows the raw sensor data of channel B1CH3. In the legend of each diagram, the subject is labeled. A total of six subjects participated in the experiment. Each subject performed four to five yawning events (A: 4, B: 5, C: 5, D: 4, E: 4, F: 5). During the measurement, 10,125 (six minutes and 45 seconds) raw data samples were collected. 2,540 (one minute and 41.6 seconds) of these samples are collected while the subject is yawning. The respective duration of a yawning event ranges from 1.52 seconds (Subject B, Yawn 5) to 7.64 seconds (Subject A, Yawn 4). The total yawn duration refers to 27 yawning events. The collected data are processed according to Section 4.1.6. An array of frequency magnitudes for each yawn and no-yawn event is used as feature vector for a support vector machine classifier (SVM). The dataset is split into 70% training and 30% test data. To review the collected dataset, Figure 4.19 shows a dimension reduction using principal component analysis with two remaining dimensions. The yawn data seems to be concentrated. Still, the data is clearly not linear separable after dimension reduction. A radial basis function (RBF) is therefore used as kernel for the SVM. The data is split into training and test data. Within the test set, 13 yawning (of 27, ≈48%) and ten non-yawning (of 49, ≈20%) samples remain. The SVM is tested with the test set. The results of these tests

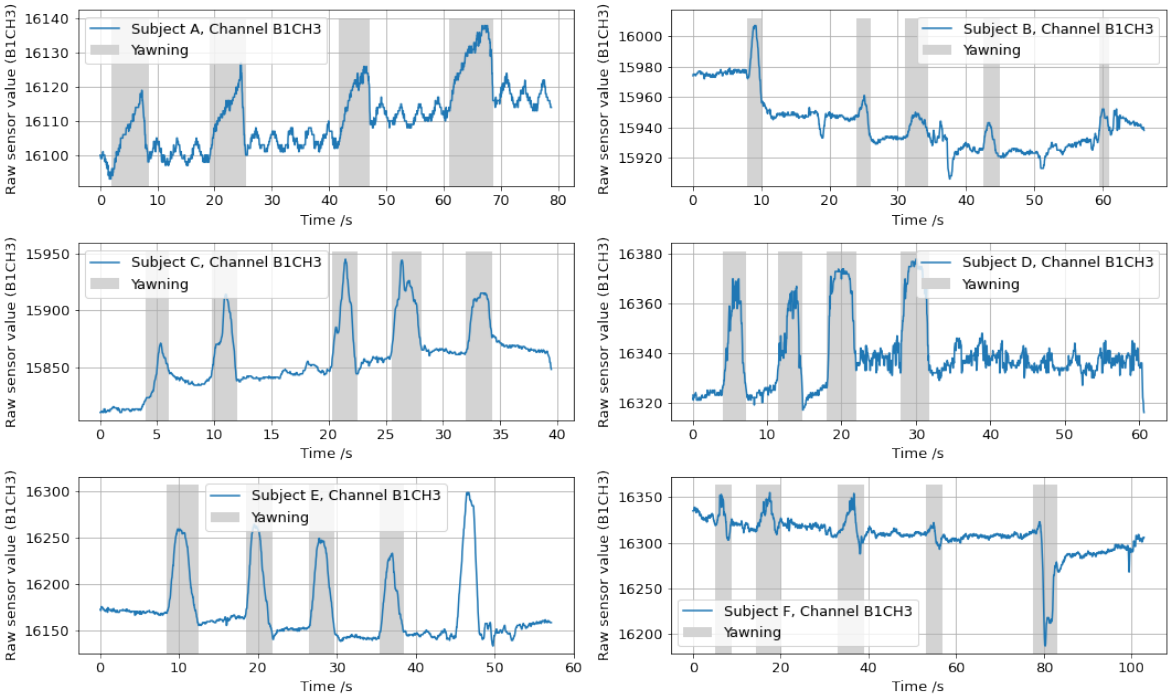



Figure 4.18.: Collected yawn samples

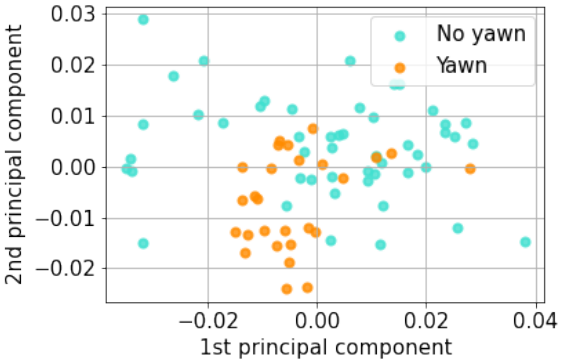



Figure 4.19.: Principal component analysis (PCA) on yawn dataset

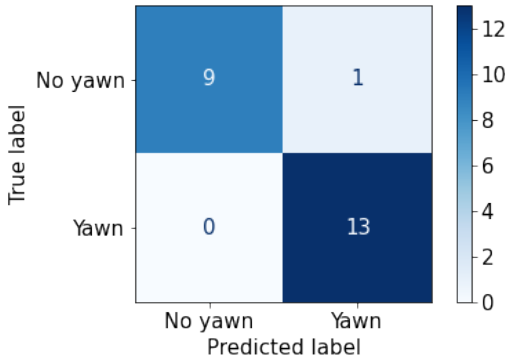



Figure 4.20.: Yawn classifier confusion matrix

| Test Subject | TPR | TNR | F1-Score |
|---|---|---|---|
| A | 1.0 | 1.0 | 1.0 |
| B | 1.0 | 1.0 | 1.0 |
| C | 1.0 | 1.0 | 1.0 |
| D | 1.0 | 1.0 | 1.0 |
| E | 1.0 | 0.96 | 0.91 |
| F | 1.0 | 1.0 | 1.0 |

Table 4.3.: Nod recognition leave-one-participant-out results

are shown in Figure 4.20. The classifier reached a true positive rate of 1 and a true negative rate of 0.9. The F1-Score equals ≈0.96. While the performance for a SVM trained with all participants is shown in Figure 4.20, a leave-one-participant-out evaluation is also conducted. In this case, the data of one participant is used as test set. The data of the remaining participants is used to train the classifier. The results of this operation are shown in Table 4.2. The results vary from subject to subject. The best F1-Score is reached testing the classifier with data of subjects D, E and F. The worst F1-Score is reached testing the classifier with data of Subject A. The mean F1-Score is ≈0.84.

The last considered symptom of fatigue measured in this project is nodding detection. An overview of the collected nodding off data from six subjects is shown in Figure 4.21. In this plot, the MinMax-scaled data are prepared according to the following equation: $y = \frac{max(MinMax)}{MinMax+0.1}$. Due to this processing, large distances between the headrest and the head are displayed as high values. Marked data with nodding events therefore start with small values and move towards a distant position of the head. The respective subject is named in the legends of the diagrams. Six subjects participated in the experiment. Each subject performed four to six nodding off events (A: 6, B: 4, C: 5, D: 5, E: 5, F: 6). During the measurement, 6,140 (four minutes and six seconds) raw data samples were collected. 507 (20.3 seconds) of these samples are collected while the subject is nodding. The respective duration of a nod event ranges from 0.4 seconds (Subject D, nod 2) to 1.28 seconds (Subject C, nod 2). The total nod duration refers to 31 nod events. The collected data are processed according to Section 4.1.6. An array of discrete differences for channels B1CH0, B1CH1, and B1CH2 for each nod and non-nod event is used

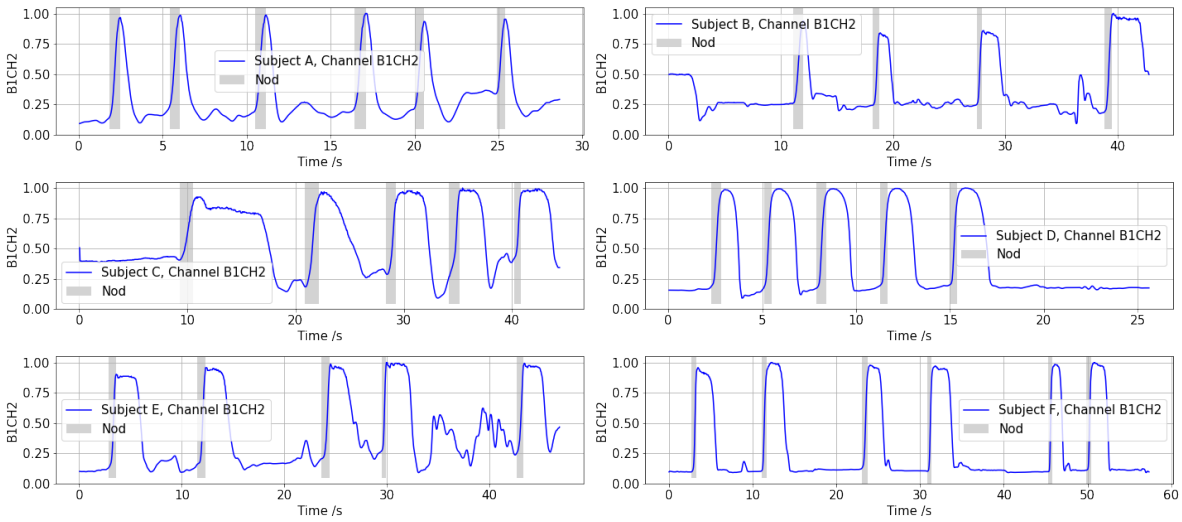



Figure 4.21.: Collected nod samples

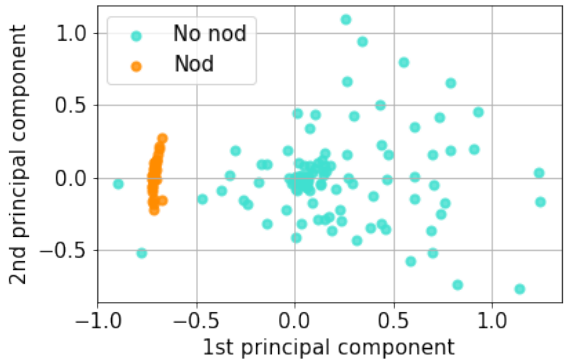



Figure 4.22.: Principal component analysis (PCA) on nod dataset

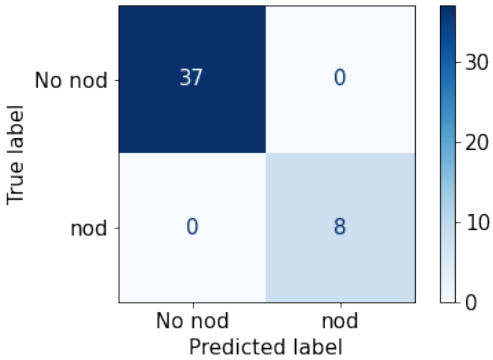



Figure 4.23.: Nod classifier confusion matrix

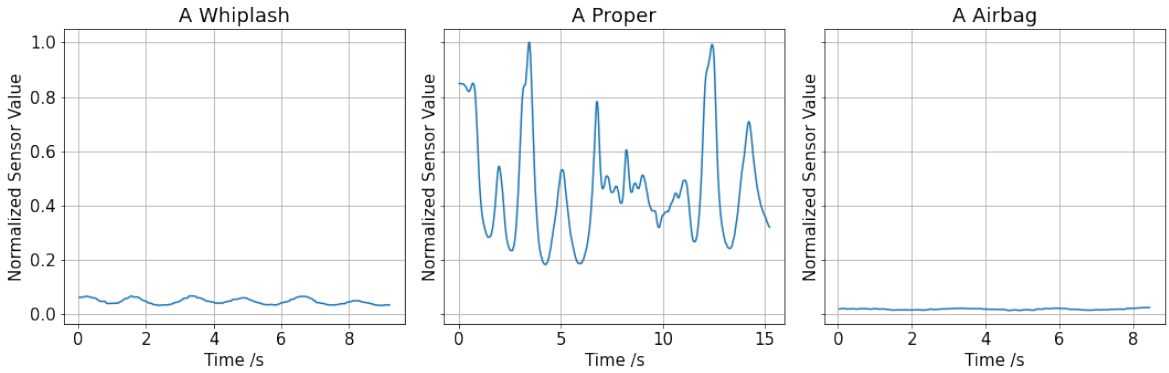



Figure 4.24.: Collected out-of-position samples for Subject A

as a feature vector for a support vector machine (SVM) classifier. The dataset is split into 70% training and 30% test data. To review the collected dataset, a dimension reduction using principal component analysis with two remaining dimensions is shown in Figure 4.22. The nod data appear to be concentrated. Nevertheless, the data are not linearly separable after dimension reduction. Therefore, a radial basis function (RBF) is used as kernel for the SVM. The data are split into training and test data. In the test set, 8 nod (out of 31, about 26%) and 37 (out of 113, about 33%) non-nodding events remain. The SVM is tested with the test set. The results of these tests are shown in Figure 4.20. The classifier achieved a true-positive rate of one and a true-negative rate of one. The F1 score is equal to one. While the performance for a SVM trained with all participants is shown in Figure 4.20, a leave-one-participant-out evaluation is also conducted. In this case, the data of one participant is used as a test set. The data of the remaining participants are used to train the classifier. The results of this process are shown in Table 4.3. The best F1 scores of one are achieved when testing the classifier with the data of subjects A, B, C, D and F. The worst F1 score is obtained when testing the classifier with the data of Subject E. The mean F1 score is about 0.99.

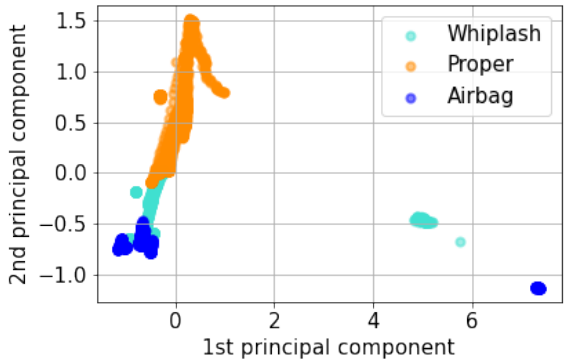



Figure 4.25.: Principal component analysis (PCA) on out-of-position dataset

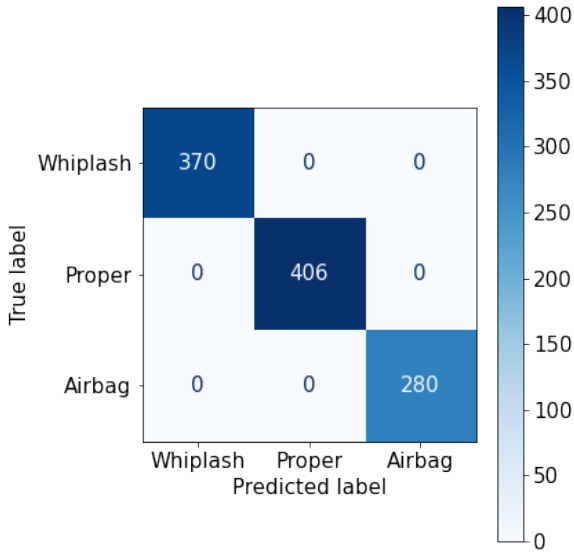



Figure 4.26.: Out-of-position classifier confusion matrix

Besides seat adjustment and attention monitoring, out-of-position detection is the next feature of the project. A total of 3,519 samples (approximately 2 minutes and 20 seconds, Whiplash: 1,188, Proper: 1,350, Airbag: 981) of data are collected at different head positions with six subjects. Specifically, subjects assume positions in which the distance from the head to the head restraint system is less than five centimeters (class: Proper), more than five centimeters (class: Whiplash), or the distance from the head to the steering wheel is less than 30 centimeters (class: Airbag). The data collected for Subject A are shown in Figure 4.24. All charts in this figure refer to channel B1CH0, which is a headrest sensor. To visualized the dataset, a principal component analysis (PCA) on the complete dataset (as shown in Figure 4.9) is processed. Using the first two principal components, the data of each class looks almost concentrated. Nevertheless, the data cannot be divided linearly. Then a support vector machine classifier is used to distinguish between the three classes. First, the whole dataset is randomly divided into 70% training data and 30% test data. 2,463 samples are used for training and 1,056 samples are used for testing. As shown in Figure 4.26, the prediction is perfect. A leave-one-out evaluation is performed. In this case, one model is trained per subject. One subject is used as test data, while the remaining subject data is used as training data. Subsequently, the evaluation metrics vary from subject to subject. The mean true-positive rate for the classifier is 0.89 and the true-negative rate is 0.95. The F1 score is 0.89 and the mean accuracy is 0.93.

In summary, every feature of the project was evaluated using a mockup created in this project. Each processing evaluation shows reasonable results. Nevertheless, mediocre results are shown in the leave-one-out evaluation of one participant. This suggests that any processing model requires data from many different individuals to satisfy robust operation. In addition, the data are collected under laboratory conditions. Features such as yawning or nodding may be more difficult to realize under real-world conditions due to the dynamics of driving, which could mask these events. In addition, subject proportions vary in terms of height and weight. Nevertheless, no obese subjects are included in the test. Therefore, the results cannot be generalized and further tests need to be performed.

## 4.2. Passenger monitoring

We discussed an application to support driver monitoring systems in Section 4.1. Symptoms and indications of fatigue detection, dangerous posture, and seat adjustment assistance were measured using capacitive proximity sensors installed in an existing vehicle structure. So, the research question RQ1 was addressed specifically for the driver's seat. To gain further insight for RQ1, another vehicle structure is used in this thesis. It is now about the child seat. Through this project, the selection of possible vehicle structures is generalized to include non-stationary vehicle structures. Similar to Section 4.1, the concept that is presented in Section 3 is applied in this project. Issues of existing systems and statistics are analyzed in Section 4.2.1. Opportunities as countermeasures for those issues are then presented in Section 4.2.2. These possibilities are to be related to symptoms and indications of the human body in Section 4.2.3 so that human emissions which could be measured with capacitive proximity sensing can be assessed in Section 4.2.4. Based on this information, the overall feasibility of this project is evaluated in Section 4.2.5. Subsequently, the actual development can take place in Section 4.2.6. A concept for capacitive proximity sensing in a child's seat is designed in Section 4.2.6. A prototype is built based on this concept. Using this prototype, data for training and evaluation of the designed models is captured so that the application can be evaluated in Section 4.2.7. Before we start with the conceptual structure, a brief overview of the contributions and considerations of this project will now be given.

The basis for this project is the fact that children must be transported safely. Securing children in a child seat is therefore indicated. The child seat's structure and restraint systems mean that children are secured in the event of an accident. Nevertheless, attention must be focused on the children and driving conditions must be monitored. However, a child seat can do more than passively prevent injuries. If the child seat is equipped with the right

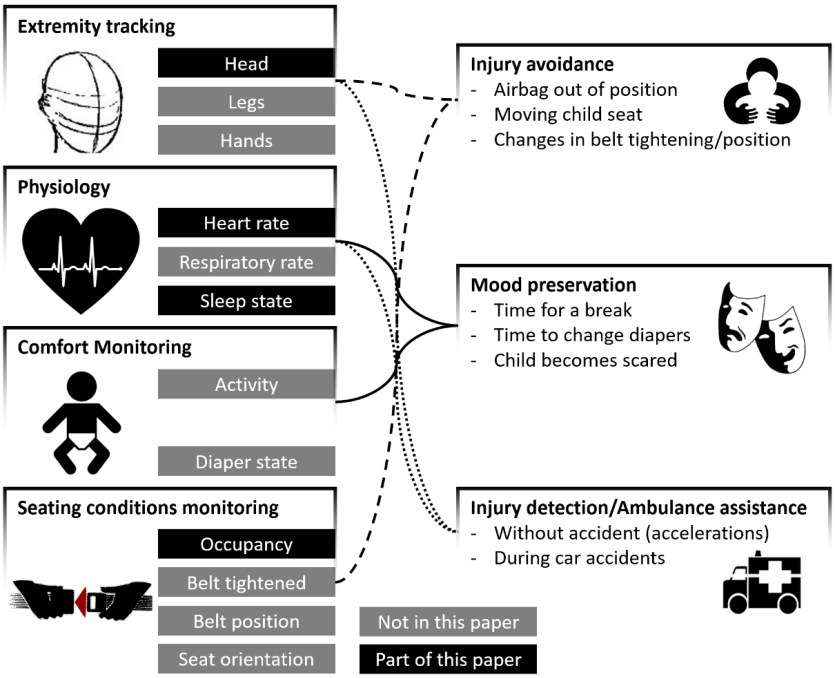



Figure 4.27.: Features that could be enabled with a capacitive proximity sensing equipped child seat [FK20a]

technology, injuries can be prevented, emergency workers can be assisted, and the child's positive mood can be maintained. These processes are illustrated on the right in Figure 4.27. While everyone wants to keep the child's mood in good shape, driving long distances can lead to unnoticed conditions. On the one hand, comfort monitoring such as detection of activity or diaper condition may indicate a break. On the other hand, altered heart and respiratory rates may indicate that the child is frightened by driving situations or multimedia systems. Each of the measures on the left side of Figure 4.27 could be enabled by equipping a child seat with capacitive proximity sensing.

### 4.2.1. Existing systems and their issues

Existing problems in the transportation of children are discussed below. Accident statistics are examined to derive problems in current child transportation systems, which form the basis for Section 4.2.2. The first considered issue emerges from a statistic as shown by Null [Nul19]. Children may be left alone in the vehicle. This leads to dangerous situations. The vehicle may heat up and children may suffer heat stroke. In 2018, a total of 52 children died due to heat stroke in vehicles and 858 children died due to heat stroke in vehicles between 1998 and 2019. While 54.0% (1998-2018) of these were forgotten by caregivers, which can happen to anyone, 18.9% (2018) of children who suffered heat stroke were knowingly left alone in the vehicle. Even though most people say they would never leave their children alone in the car, situations that require immediate assistance can lead to difficult decisions. For example, when someone arrives at an accident, first aid must be provided. The decision must then be made whether to leave the child alone in the car to provide first aid. So, it is possible to intentionally leave your child unattended. There are several problems that can be derived from these statistics. One problem is that children can be forgotten in vehicles. Another problem is that regardless of whether children are intentionally left behind, there is no monitoring of the child's condition to check and alert responsible parties. Because of the issue that children may be left alone in cars, a lot of research is conducted on child occupancy recognition [AG12, LJW*07, RG13, DLT*16] to avoid this. This prevents temperature-related heatstroke, as the child is no longer left alone in the car. Occupancy recognition systems are based on various sensor systems. For example, capacitive proximity sensing is used by Ranjan et al. [RG13]. To detect the occupancy of a child seat, the sensors are installed in it. These systems consist not only of occupancy detection. Actions that can take place when a child is forgotten are also explored. An exemplary system is implemented by Aneiros et al. [AG12]. A controller is installed in the vehicle, which is able to control lights, ignition switch, alarm system and other vehicle components. Thanks to the controller, the system can inform the driver if a child has been left in the vehicle. It can also open the doors to allow the child to be quickly rescued. To do this, the system requires child presence sensors. When these sensors detect an occupied child seat, an alarm is triggered until the driver is back in the car. The system also starts the car's air conditioning if the delay between the seated child and seated driver is greater than two minutes. Another child presence detection system is presented by Lusso et al. [LJW*07]. Two force sensors and a wireless video camera pointed at the child seat are built into the vehicle. The presence of the child is detected with these force sensors. In addition, the video camera is pointed at the child's face. The video camera is installed to solve the second problem of children left behind: the condition of the child. All sensors are included in the vehicle electrical system. Similar to Aneiros et al., Lusso et al. also sound the alarm when a child is left behind. The system is tested in a real vehicle. Two temperature sensors are used to test the system behavior at different temperatures. Occupancy detection systems address the problem of children unintentionally left in cars. However, the systems found use only capacitive proximity sensing for occupancy detection, although information about the child's condition could be helpful. Lusso et al. already point out that additional information is needed for safe transportation of the child. Nevertheless, their camera must be installed in the interior of the vehicle. This makes the system obtrusive. A camera pointed at children may also cause privacy issues.

In addition to children left behind, injuries are also caused by improperly seated children in child seats. 1,247 data samples from children in child seats are collected by the NHTSA [DL03]. If the adjustment of the child seat can increase the risk of injury, this is referred to as critical misuse. For example, for forward-facing child seats, more than 58% show critical misuse due to loosely fastened harness straps. More than 18% show critical misuse due to incorrect position of the harness straps. So, the issue here is that improper adjustment of the child seat can lead to injury. Incorrect adjustment could be detected before the ride begins. Nevertheless, the settling behavior of thick clothing can loosen the hold of the straps. So, this is about the improper adjustment of the harness and the unmonitored behavior of the harnesses during the ride. As mentioned earlier, these issues can lead to serious injuries in the event of an accident. In general, high accelerations can cause injuries to the child's extremities. Hence, researchers like Mazurkiewicz et al. [MBK*18] work on improved passive safety features to decrease the acceleration of for example the head of a children in case of an accident. Minimizing the consequences of an accident is one approach. Nevertheless, these systems do not provide information about the child's actual condition. In other words: While injury prevention aims to prevent injuries, injury detection can support the selection of medical therapy. In particular, head acceleration can indicate injury.

If these above issues can be addressed, the safety of children while driving can be improved. One problem is that children can be left in the car. Heat stroke can be caused when children are alone in the car. Improper use of child seat belts can also cause serious injuries. In particular, high extremity acceleration is the cause of these injuries. Extremity tracking may point to the usage of image processing. Nonetheless, a line of sight and distance between the child and the lens is required when cameras are used. Thus, cameras would need to be incorporated into the interior design of the vehicle. Cameras could also lead to privacy issues. Additionally, physiological states could be measured with wristband sensors. Since people tend to forget to put on a wristband, this is prone to error. A summary of the issues being addressed in this project is shown on the right in Figure 4.27. Mood preservation has not yet been named. There are few studies and statistics on mood maintenance in vehicles. Nevertheless, a good mood child is beneficial for everyone.

### 4.2.2. Opportunities

Several issues concerning the transport of children in vehicles are named in Section 4.2.1. We now discuss opportunities or countermeasures to tackle those issues. As already stated, a summary of the issues is shown on the right of Figure 4.27. In general, injuries that can be caused by an incorrect position of the child or the child seat and incorrectly fitted child seat belts should be avoided. Possible injuries to the child in the child seat should also be recognized, for example, to call the ambulance. Additionally, mood maintenance is mentioned. The countermeasures considered for these points are shown on the right in Figure 4.27. By recognizing injuries and preventing them, supervisors can respond to the child's condition. Because injuries are caused by high accelerations, extremity acceleration monitoring is considered an aid to injury prevention. In particular, severe injuries could be detected or prevented by tracking the child's head. As research has already addressed, occupancy detection can prevent children from being unintentionally left behind and thus reduce the risk of heat stroke. Regardless of whether the child is intentionally left in the car, the driver could return early if mood and condition monitoring systems sound an alarm. For example, heart rate and sleep status could be monitored, as well as the child's activity and diaper condition. Other countermeasures are mentioned on the left side of Figure 4.27. This project is focused on a subset of features. Besides the recognition of features named on the left of Figure 4.27, conditions of the system are named as potential issues in Section 4.2.1. Privacy should be maintained by the system. In addition, the system should be integrated unobtrusively so that the interior design is not affected by the device. In addition, the system should be integrated into a vehicle structure so that it cannot be forgotten by the driver.

### 4.2.3. Symptoms, indications and human emissions

Several countermeasures for the issues presented in Section 4.2.1 are named in Section 4.2.2. We now discuss specific emissions of the child in the child seat associated with these countermeasures. It is shown by Eppinger et al. [ESB*99] that head injuries can be estimated from head acceleration and exposure time. Acceleration and exposure time can be derived directly from the head position. The child head position is therefore considered as a required human emission. Injuries can also be avoided by occupancy detection. For example, the human emission for occupancy detection is the presence of the child on the seat. This could be further extended by occupancy detection systems that detect heart rate or respiration rate, so that the emission in this case is the movement of the child's heart and chest. Heart rate, and thus human emission of heart motion, can provide emotion recognition, as shown, for example, by Michels et al. [MSC*13]. Another symptom that gives hints for mood changes is the sleep state. The sleep state can be derived of the activity of the child as shown by Morgenthaler et al. [MAF*07]. So, the child's movement is the human emission for sleep detection. In summary, the selected human emissions are the movements of the child's body for sleep state detection, the head position for injury prevention, and detection of the heartbeat.

### 4.2.4. Physical characteristics and related work

In Section 4.2.3 we identified several human emissions that need to be monitored in this project. In general, these emissions are based on the movements of the human body, which can be detected with capacitive proximity sensors, as shown in Section 2.1. Head position detection should therefore be possible with the help of these sensors. Related research already demonstrates the application of capacitive proximity sensors for detecting the occupancy or position of child seats. In particular, a system for detecting the position of child seats has been developed by Smith [SG99]. Four sensing electrodes are integrated in a vehicle passenger seat. These are used to perform 16 individual measurements. The seat can be equipped with an additional child seat. Based on the measurements, four classes of seat occupancy can be distinguished. These classes are "empty," the passenger seat is empty; "person," there is a person in the seat; "FFCS," there is a forward-facing child seat in the passenger seat; and "RFCS," there is a rear-facing child seat in the passenger seat. Smith states that the success of the system led to a collaboration with automotive supplier NEC Automotive Electronics. NEC Automotive Electronics [JOOS01] patented a similar system. Even though this system is not directly integrated into the child seat, this system shows a first connection between capacitive proximity sensing and child seat monitoring. A more challenging human emission is heart rate detection or heart motion. The human body is mostly water, and the heart is embedded in the human body. Capacitive proximity sensing may therefore not be able to directly measure heart contraction. Nevertheless, a measurable body displacement due to the heartbeat can be detected, as shown by Michahelles et al. [MWS04]. Since the movement of the body affects the output value of the capacitive proximity sensors, these movements could be measurable.

As already mentioned, motion of the child body can provide information about the sleep state. Methods such as Actigraphy, in particular, are used to distinguish between sleep phases [MAF*07]. Actigraphy is a measure to assign subject movements to sleep phases. Since movements can be tracked with capacitive proximity sensing, this should be feasible. Activity tracking and limb tracking using capacitive proximity sensing is already feasible in several applications [BFW15, BSF15, FDKK20, FK17a, FK17b, FK18, FK19].

Even though capacitive proximity sensing is not directly used for human emissions from a child in a child seat, related applications are found for the proposed functions that enable similar functions in different environments. The physical properties of capacitive proximity sensing are also promising, allowing detection of object motion that is closely related to most human emissions. Evidence for the rating of the feasibility in Section 4.2.5 is therefore given. Vehicle structures can additionally be found near the human emissions so that functionality can

be enabled. Although capacitive proximity sensors can detect the desired human emission, the human emissions presented are not the only emissions indicative of conditions such as sleep state and heart rate. There are, of course, other indications that could be measurable with other sensor systems. Nonetheless, the specific human emissions in Section 4.2.3 are picked as a subset that can likely be enabled with capacitive proximity sensing. As there are more symptoms and indicators for the specific features, they could also be enabled by more sensor systems, so capacitive proximity sensing can support a sensor-based system, with multiple categories.

### 4.2.5. Feasibility, vehicle structure and benchmarking

We identified human emissions, which could be detected with capacitive proximity sensing, in Section 4.2.4. This is supported by various related works dealing with specific sub-problems of this project also outside the automotive environment. The detection of the presented features for the application is therefore considered feasible. Thus, a suitable vehicle structure can be selected for sensor deployment. The interior roof of the vehicle could be the basis for a non-contact sensor system directed at the child seat. In this way, all extremities of the child in the child seat could be monitored. For example, a camera could be installed. However, a vehicle structure is chosen that is not tied to the vehicle, but to the device that must be installed in the vehicle when children are transported: the child seat. If the sensors are attached to the child seat, the system can function independently of the actual vehicle. It would even be possible to change cars and use the child seat in another vehicle. The child seat is also the closest vehicle structure to any part of the child's body. Now that a suitable set of vehicle structures has been found, specifically the interior roof and the child seat, selected sensor systems can be benchmarked with capacitive proximity sensors. Before the sensors can be selected, the application constraints and weights must be defined. The biggest limitations for resolution come from heart rate detection. According to Ramachandran et al. [RS89], the movement of the chest has an amplitude range of ≈0.2-0.5mm. The required resolution is therefore less than one millimeter. The weighting for this metric is set to medium. Since accelerations of the head are to be tracked, a sufficient update rate of 20Hz, which should be close to real time, is considered appropriate. The weighting for this metric is set to medium, as higher update rates could improve detection. If the sensors are installed in the child seat, the detection range is less than 10 centimeters based on detection of limb movement. When the sensors are installed in the roof of the vehicle, the detection range increases to less than one meter. The weighting for detection range is set low because higher detection ranges should not improve the system. In terms of unobtrusiveness, the weight is set to high. Since the sensors monitor the child's condition, no privacy-threatening data should be collected. Also, the interior design should not be affected by the system. Since this project is in the prototyping stage, the processing and calibration complexity is set to medium importance. Robustness and disturbance frequency are set to a high value, since safety-related functions are to be developed. Subsequently, unique limitations are neglected. Even if the sensor system is to be integrated only into the child seat, there are few sensor systems that can enable all functions without additional integration into the vehicle. By neglecting the unique limitations, sensor systems like cameras can be compared in the benchmarking process. The final weight vector for the application is: $\vec{w} = (0.5\ 0.5\ 0.25\ 1.\ 0.5\ 0.75\ 0.75\ 0.5\ 0)^T$

We now select sensors that can be compared to capacitive proximity sensors. The same camera that was used in Section 4.1 is selected here. Other sensor systems such as pressure sensors are neglected. Occupancy detection could be enabled by pressure sensors. However, extremity tracking could limit the use of pressure sensors since contact is not always given by the movement of the child in the child seat. The camera achieves an update rate of 25 to 50 Hz at a resolution of 320x240 pixels. The specific resolution of the camera on the child's chest is difficult to estimate, but is estimated to be more than 1 mm. Therefore, the resolution is set to a low value while the update rate is set to a high value. The detection range is set to a high value because the camera can detect at distances greater than one meter. The unobtrusiveness is set to a low value. Cameras that track the child's head can capture facial images. If the camera is integrated into the interior roof, this may also interfere with the interior

design. Processing complexity is rated good. Robustness is still rated medium. Since the image processing can be disturbed by the lighting conditions, the disturbance frequency is rated as low. Next, the calibration complexity is rated medium. The final rating vector for cameras is: $\vec{r} = (0.25\ 1.\ \ 1.\ \ 0.25\ 0.75\ 0.5\ 0.25\ 0.5\ 0.5)^T$. Capacitive proximity sensors are the second considered sensor system. According to Puppendahl [GP15], capacitive proximity sensors show a resolution of less than one millimeter at distances less than 25 millimeters. Since this is sufficient for heart motion detection, the resolution is classified as medium. The update rate of the selected sensor system is 25Hz. Therefore, this metric is classified as medium. Additionally, the detection range is set to a high value. According to Puppendahl, capacitive proximity sensors are capable of having a resolution of less than ten millimeters at a distance of 15 centimeters. That should be sufficient for detecting the head position. The unobtrusiveness is rated as good. No facial images can be captured and the sensor technology can be integrated invisibly. The processing complexity is rated medium. The actual complexity will need to be evaluated in this project. Robustness is still set to medium, as the sensors could be disturbed by changing temperature and humidity conditions. Disturbance frequency is rated medium for the same reasons. Finally, calibration complexity is set to medium. The final evaluation vector for capacitive proximity sensing is: $\vec{r} = (0.5\ 0.5\ 0.75\ 0.75\ 0.5\ 0.5\ 0.5\ 0.5\ 0.5)^T$. Based on these ratings and the weighting for the application, the benchmarking score for the camera-based system is 0.49 and for capacitive proximity sensing is 0.57. Therefore, the capacitive proximity sensing system wins the benchmark when they are compared to cameras for this application.

### 4.2.6. Develop

We have identified in Section 4.2.5, that the required functions of this project can be enabled with capacitive proximity sensors. Capacitive proximity sensors also won the benchmarking against a hypothetical camera-based system. Additionally, the child seat was selected as a suitable vehicle structure. Capacitive proximity sensors must therefore be integrated into this structure. We now investigate each required function and will see how these can be enabled with capacitive proximity sensors. The functions are seat occupancy recognition, heart rate recognition, head position recognition and sleep state recognition. A processing model is developed for each feature, which is used as the basis for identifying a sensor topology. We will integrate this topology into an ordinary child seat. To parameterize the processing models, we will also see how the data is labeled. This is necessary to prepare for data collection and model evaluation in real test drives. The first feature considered is occupancy detection. Occupancy detection aims to prevent heat stroke or forgotten children in child seats. Occupancy consists of two classes. The person can be sitting in the seat, which is classified as OnSeat, or the seat can be empty. This is classified as NotOnSeat. This is a binary classification problem and a decision tree classifier is used. Since it is assumed that the distance between the sensing electrodes and the person is the main influence on the capacitive proximity sensing measurement data, the feature vector of the decision tree classifier consists of the raw output of the capacitive proximity sensing data. As used in existing passenger seat occupancy systems [GZBB09], sensors are required below the subject's pelvis. This is nevertheless a minimum restriction. If further detection models require more electrodes, these are also integrated into the feature vector.

The next considered feature is the heart rate recognition. As shown in Figure 4.27, heart rate recognition is an essential task for emergency assistance. Moreover, changes in heart rate can give hints about the mood and emotions of subjects [JA90]. Thus, heart rate information is helpful for mood preservation. The human body consists of mostly water and the heart is embedded into the human body. Thus, capacitive proximity sensing may not enable to measure heart contraction directly. Nonetheless, measurable body displacement due to heartbeat can be discovered [MWS04]. Body displacement affects the output value of capacitive proximity sensing. Those displacements ought therefore to be measurable. Heart rate measurement is enabled if the subject is on the child seat (Occupancy recognition: OnSeat). Heart rate recognition is therefore only active in OnSeat state. Further, heart rate results from the frequency of heart contraction. Frequency becomes measurable in time series.

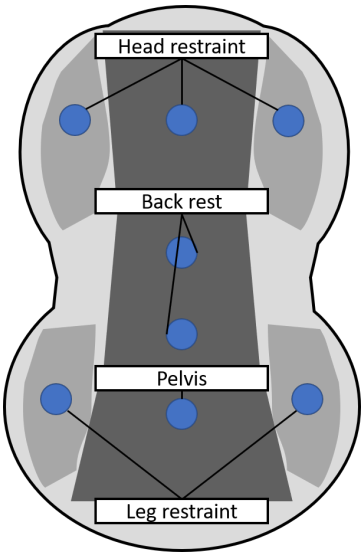



Figure 4.28.: Designed sensor topology [FK20a]

Time series of capacitive proximity sensing data is therefore considered mandatory. Subject back movement is expected to be low while subject is OnSeat. Thus, capacitive proximity sensing data of sensing electrodes in the child seat back rest is included. Even though, subject pelvis movement may not contribute to heart rate, since it is not close to subject heart, vehicle vibrations may be indicated by pelvis sensors. Pelvis sensors are therefore included. The heart rate at time t is considered as a result of a previously analyzed heart movement analysis. Thus, frequency magnitudes of ten seconds time intervals capacitive proximity sensing data are used as basis for model features. Due to the continuous nature of the heart rate, a regression model is chosen. In particular, a neural network (MLP) with one hidden layer is selected. The hidden layer consists of ten neurons.

The next feature considered is head position tracking. As shown in [ESB*99], head injuries can be estimated from head acceleration and exposure time. Acceleration and exposure time can be derived directly from the head position. The detection of the child's head position must therefore be enabled by this application. The center of the face (nose) is used as a target. Sensors in the headrest of the child seat should be able to detect the head position. We focus on the translational positions of the subject's head. With different head postures, different outputs from the pelvis and backrest sensors are expected. Additional sensors in the child seat should therefore provide an estimate of head rotation. It is expected that the difference of the capacitive proximity sensors of the headrest is the main indicator for head displacement. Therefore, the feature vector for the regression model is based on the difference between each capacitive proximity sensor output. This would mean, for example, that a feature vector entry is formed by the difference between the left and right headrest sensor outputs. Due to the continuous nature of head position, a random forest regression model is chosen.

The last feature considered is sleep state detection. Similar to heart rate detection, the frequencies of capacitive proximity sensing data are used. The frequency magnitudes of a time window of ten seconds of capacitive proximity sensing data are calculated. In this way, comparability between heart rate and sleep detection performance will be enabled. The same capacitive proximity sensing topology as for heart rate detection is subsequently considered suitable. To improve activity detection, capacitive proximity sensing electrodes will be integrated into


Figure 4.29.: Used child seat with sensors [FK20a]

the child seat leg rest. Based on the models for each specific feature, the required sensing electrodes will be collected. The measurement on the subject's pelvis is needed for occupancy detection, the measurement on the seatback is needed for heart rate detection, the measurement on the headrest is needed for head position detection, and additional sensors on the leg rest are needed for sleep state detection. The spatial electrode topology is derived from these requirements. It is shown in Figure 4.28. Sensing electrode positions are indicated by blue circles. All sensors must be placed under the child seat cushion. If the existing cushion is not sufficient for the placement of the electrodes, the electrodes must be placed under non-conductive parts of the child seat structure. Eight capacitive proximity sensing electrodes are required. Since real systems provide discrete data, an appropriate sampling rate must be determined. Obviously, heart rate is a frequency-based biometric feature. That is why the selection of the sampling rate of capacitive proximity sensing is based on heart rate detection. In the following test runs, the age of the test subject is about 1.5 years. According to O'Leary et al. [OHLP15], the heart rate for the 25th and 75th percentiles of an 18-month-old child falls within an interval between 116 and 136 beats per minute (bpm). If this is mapped to beats per second (bps), the heart rate should be between 1.93 bps ($HR_{min}$) and 2.27 bps ($HR_{max}$). This must be covered by the heart rate detection application. The selected capacitive proximity sensing device is capable of monitoring eight sensing electrodes [GPBB*13]. Each measurement channel output is sampled at 25 Hz. This results in an oversampling factor of about 11 compared to $HR_{max}$. The Nyquist rate is therefore exceeded [Par16]. One sensing electrode must be attached to the child seat for each measurement channel. Unprocessed circuit boards (copper, epoxy) are used as capacitive proximity sensing electrodes and shielding. Each electrode has a length of 10 cm and a width of 16 cm. This results in an area of $0.016m^2$. To minimize deviating temperature effects, a uniform electrode arrangement is chosen. Due to the structure of the circuit boards, the electrodes for capacitive proximity sensing and the shielding area are congruent.

These sensing electrodes have to be installed in a prototype. Eight channels for capacitive proximity sensing and the associated circuit boards are mounted on an ordinary child seat. The child seat and the sensing electrodes are shown in Figure 4.29. As shown in Figure 4.29, the seat cushion is removed completely for installation. The available space in the leg rest area was not sufficient for electrode mounting. As shown in Figure 4.29 (right), leg-related electrodes are placed under the seat skeleton. The seat cushion is then mounted back onto the seat (Figure 4.30).

We have now equipped an ordinary child seat with capacitive proximity sensors. Labeled data is needed for the evaluation of the processing models. The prototype is installed in a normal car for real test drives. Therefore,


Figure 4.30.: Test setup camera view cut out [FK20a]

the test drive monitoring system in the car must be able to record the subject's activity, occupancy, sleep state, and heart rate. For the acquisition of the true heart rate, an optical heart rate sensor [Pol19] is used. The sensor is labeled OH1 in Figure 4.30. Occupancy detection, head position detection and sleep state detection are labeled using image processing. The images are provided by a camera. The camera is mounted on the vehicle's interior roof. It points in the direction of the child seat. The view of the camera is shown in Figure 4.30.

While the labeling system for heart rate detection provides the heart rate directly, the other features have to be derived from the recorded videos. Image processing, especially face recognition, is used to determine the horizontal head position [Ope20a]. An example of face recognition for labeling is shown in Figure 4.31. Since the relative position of the camera and child seat is not fixed, a fixed reference point of the child seat is added. A label on the child seat is used as a stable reference point. The reference points are collected from random image samples. Therefore, the influence by the movement of the child seat due to the course of the test drive (subject movements, vehicle vibrations, rotation due to the winding road) should be minimized compared to a single reference point. The face recognition algorithm used is not robust throughout the measurement. The labeled data is therefore filtered for valid recognized face positions. Only recognized face areas within region of interest (Figure 4.31: "ROI"), are used. The remaining recognized faces are then filtered according to their area. Only faces between the 35th and 65th percentile of all faces remain. The detected horizontal face position is subtracted from the position of the reference point. Then, half of the width of the face area is added to determine the face center point. This results in the target labeling as shown in Figure 4.31. The face detection algorithm used does not work in all lighting conditions. Only frontal faces are recognized and the facial profile is not tracked. To include more labels, especially from positions at the seat boundaries, manual labels are added. These manual labels consist of the position of the subject's nose.

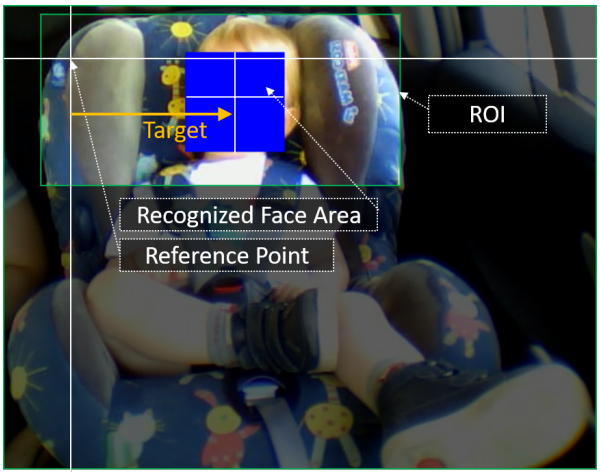



Figure 4.31.: Head position labeling [FK20a]

### 4.2.7. Evaluate

Estimators for all characteristics considered were defined in Section 4.2.6. The required sensor topology is integrated in an ordinary child seat. This child seat is installed in a vehicle so that data can be collected for training and evaluation. We will analyze the collected data for each feature and then use it to train and evaluate the models. The data collected consists of ten test drives with a heart rate sensor, capacitive proximity sensors, a camera and a temperature sensor. More than nine hours and more than 600 km are recorded. The video data is manually analyzed to characterize occupancy and sleep state. The distribution of occupancy and sleep state among the test drives is shown in Figure 4.32. Awake and asleep states show approximately balanced durations. An unbalanced duration for on-seat and off-seat is indicated by a ratio of about 36 to one. We now examine the first feature: seat occupancy detection. The real transition of subject on seat (OnSeat) and not on seat (NotOnSeat) is fuzzy. Therefore, a buffer of ten seconds before and after each transition is not considered. 8.6 hours of OnSeat and 16.5 minutes of NotOnSeat data are collected. The raw data from all eight channels are used as the model input vector. The complete data set consists of 776,000 OnSeat and 25,000 NotOnSeat samples. These samples are randomly divided into 50% training and 50% test data. Then, a decision tree classifier is trained with training data to distinguish between OnSeat and NotOnSeat. The classes for the test data are subsequently predicted by the classifier. Evaluation of the predictions yields a true(T)-positive(P) rate of about 1 (P: 387,057, TP: 387,047) and a true(T)-negative(N) rate of about 1 (N: 12,457, TN: 12,444). The presence of the child in the seat activates other recognition processes such as heart rate detection.

Only data labeled OnSeat is considered for heart rate detection. Except test ride one, all test rides have one single OnSeat phase. As shown in Figure 4.32, test ride one hast two OnSeat phases. Since less than four minutes are acquired in the first phase, this phase is omitted. Acquired heart rate data is synchronized with capacitive proximity sensing data via time stamp information. Subsequently, the data from the capacitive proximity sensors is processed according to Section 4.2.6. A frequency spectrum remains. The complete dataset is visualized in Figure 4.33. The data is grouped by heart rate data. The frequency magnitudes of each group are then averaged. This is repeated for all channels. Each circle sector represents a channel, starting from the channel label to the next label in a counterclockwise direction. The angle of each sector represents the frequency. For example,

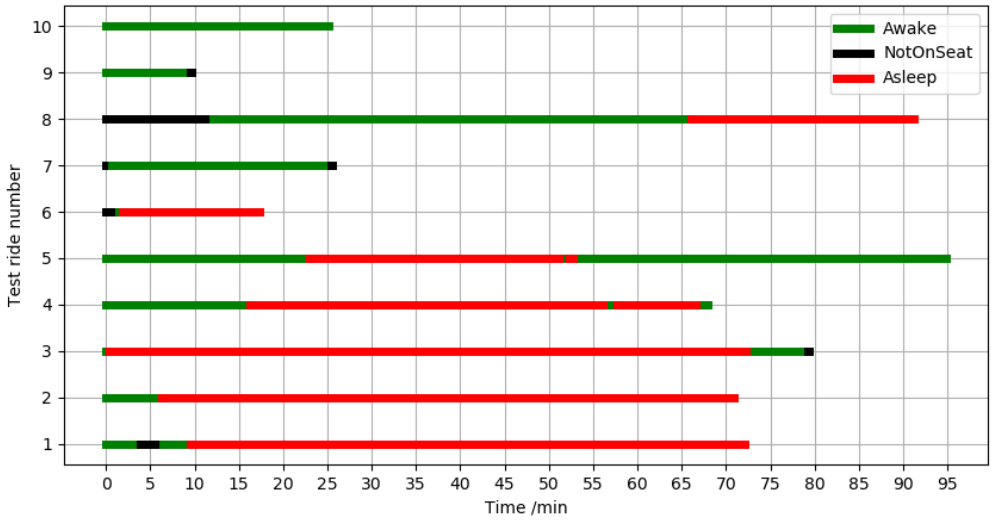



Figure 4.32.: Subject states during measurements diagram [FK20a]

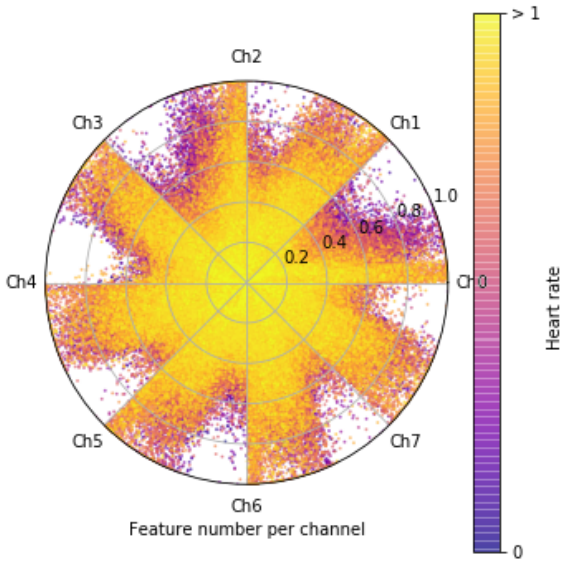



Figure 4.33.: Heart rate recognition feature vector data [FK20a]

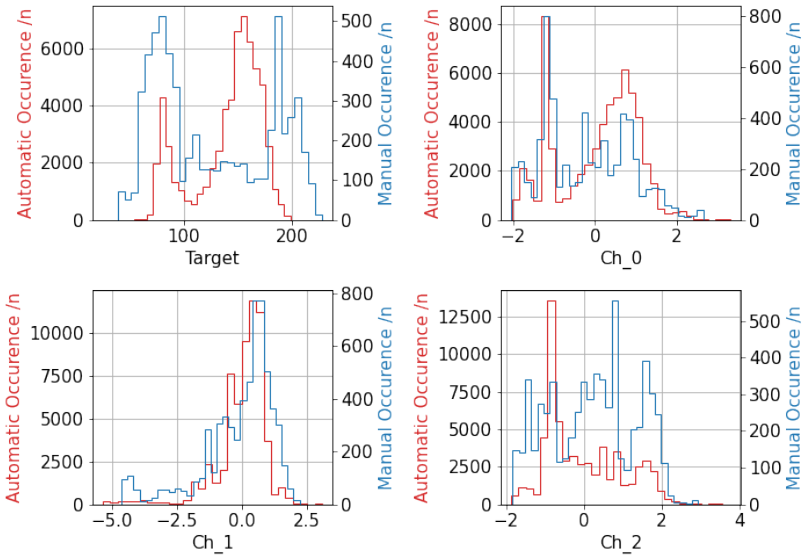



Figure 4.34.: Head position dataset value distribution

frequencies of channel one range from 0 Hz at label "Ch1" (angle = 45°) to 12.5 Hz at label "Ch2" (angle = 90°). The colors represent the MinMax scaled heart rate value. A neural network regression model is trained and evaluated. The data is split into 75% training and 25% test data. Then, the training data are resampled to obtain a uniform distribution of values. A mean absolute error of 6.2 bpm is measured. A great difference between training performance ($R^2 \approx 0.85$) and test performance ($R^2 \approx 0.55$) points to overfitting.

The next considered feature is the head position recognition. The labeled data is processed as described in Section 4.2.6. The data set is thus composed of automatically and manually labeled data. The distribution of the target variables and the values of the headrest sensors are shown in Figure 4.34. A total of 67,666 samples of labeled head position data are collected. A random forest regression model is trained and tested with this dataset. Training and testing are performed using ten-fold cross-validation. A mean coefficient of determination ($R^2$) of 0.95 is measured and the mean absolute error (MAE) is 3.87 pixels.

We then evaluate the sleep state detection. Recorded data is therefore labeled as presented in Section 4.2.6. 261.61 minutes asleep and 185.62 minutes awake are recorded. The distribution of sleep states during test rides is shown in Table 4.4. Due to the fuzzy transition between sleep and awake, a buffer of 20 seconds is omitted at each transition. Comparable features for heart rate detection are generated. A time window of 10 seconds (250 samples) is used. The dataset is comprised of 1,235 awake (P) and 1,737 asleep (N) samples. Using this dataset, a random forest classifier is trained. Data of all test runs is split into 80% training and 20% test data. Before the training, the class distribution in the training data set is balanced. A true (T) positive (P) rate of about 0.93 (P: 242, TP: 226) and a true negative (N) rate of about 0.91 (N: 319, TN: 291) is measured for the test data predictions.

All the characteristics of this project to be recorded were evaluated. Similar features for sleep detection and heart rate detection are selected so that the results of the models can be compared. The data from these models are therefore now compared and plotted in a violin plot, which is shown in Figure 4.35. A violin plot has

| Test run | Awake | Asleep |
|---|---|---|
| All | 1,235 | 1,737 |
| 1 | 36 | 369 |
| 2 | 36 | 258 |
| 3 | 34 | 420 |
| 4 | 95 | 283 |
| 5 | 379 | 176 |
| 6 | 1 | 90 |
| 7 | 146 | 0 |
| 8 | 304 | 141 |
| 9 | 52 | 0 |
| 10 | 152 | 0 |

Table 4.4.: Sleep recognition processed sample count

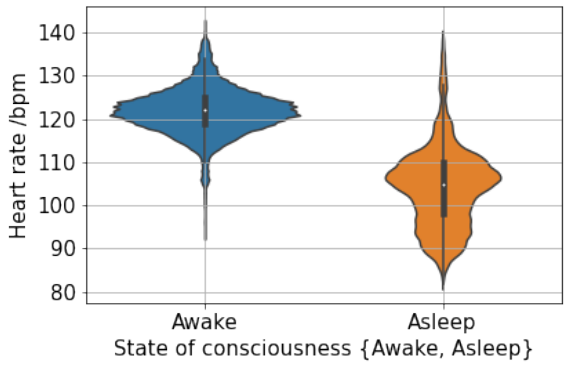



Figure 4.35.: Heart rate and sleep state distribution [FK20a]

similarities to a box plot. The occurrence of data points for each label is represented as blue and red bordered areas. Median values are represented by a white dot in the center of each violin. The interquartile range (IQR) is shown as a black thick vertical bar. Values that are within the first quartile have a value less than the IQR. Values that are not within the third quartile have a value greater than IQR. A range between the first quartile minus 1.5 times IQR and the third quartile plus 1.5 times IQR is represented by the thin vertical lines. Outliers can be indicated by values larger or smaller than this line. As shown in Figure 4.35, the median heart rate values are: awake about 122 beats per minute (bpm) and Asleep about 105 bpm. Within the IQR for awake and asleep, no intersection of heart rate is displayed. Nevertheless, data intersections between sleeping and awake are displayed for regions outside the IQR. These intersections are not considered outliers. Due to the data distribution in Figure 4.35, heart rate recognition can be based on similar model observations as sleep state recognition. Nevertheless, there are also changing heart rates in the same sleep state. A correlation between sleep state detection and heart rate seems plausible for healthy people. The correlation shown in Figure 4.35 seems therefore valid. Therefore, the assumption that heart rate detection is mainly based on sleep state detection cannot be rejected. Nevertheless, heart rate detection could be improved by additional sleep state detection data. Likewise, sleep state detection could be improved by additional heart rate detection data. In both cases, the models could benefit from the respective observations. The designed heart rate detection model shows a mean absolute error of approximately 6.2 bpm. Although an error of about 6.2 bpm seems to be acceptable for a barely optimized model, an inconclusive verdict on heart rate detection is strengthened by a coefficient of determination of about 0.5 obtained for the heart rate regression model. Two procedures could evaluate heart rate detection with confidence. First, the measurement must be extended to different subjects. Several subjects may have different heart rates at rest and during activity. Different heart rate characteristics during similar exercise may rule out a direct correlation between sleep state and heart rate. This may also improve model performance. The sensor topology could also be extended to include sensing electrodes in the seat belt. This configuration would allow measurement in shunt or transmit mode [SG99]. Sensors near the subject's chest could allow micro-movements to be distinguished from other body movements, as demonstrated by Michahelles et al. [MWS04]. Contrary to heart rate recognition, head position recognition, occupancy recognition and sleep state recognition show good performances.

## 4.3. Discussion

Chapter 4 aims to answer research question RQ1: *How can we use existing vehicle structures to enhance or substitute vehicular human machine interfaces using capacitive proximity sensing?* Two applications were developed and evaluated to provide information about driver and passenger status, respectively. Both applications, the enhanced driver seat for driver monitoring and the enhanced child seat for child monitoring, were developed according to the concept presented in Section 3.1. Because of the concept, each application has a basis in the real world and therefore addresses existing problems to increase driver and passenger safety and comfort. Existing vehicle structures are used in both systems. By incorporating capacitive proximity sensors into these structures, a vehicle-side human machine interface is established. Research question RQ1 is thus directly addressed. Nevertheless, it cannot be conclusively assessed whether these applications merely complement or even replace the human machine interface in the vehicle. Essential functions such as sleep state detection, out-of-position detection, and drowsiness detection are provided by both applications. Combining these systems with other sensor technologies such as image processing, however, could increase detection rates. It is therefore a matter of specification whether capacitive proximity sensing is considered sufficiently powerful for a system. Both systems have their advantages and disadvantages. The following two paragraphs will discuss the individual applications.

The first application presented is a driver's seat equipped with capacitive proximity sensing. It is presented in Section 4.1. The system is based on sixteen capacitive proximity sensors with different electrode sizes. Each sensing electrode is invisibly integrated into the seat structure. The data from these sensors is used through various processing models to detect the anthropometry and physiology of the driver. In this way, seat adjustment can be assisted to ensure that the driver is seated in an appropriate posture. In addition to seat adjustment, systems can also be supported to assess driver fatigue. More specifically, symptoms of fatigue or inattention such as suspicious steering speed, yawning, nodding and gazing are detected. It should be noted that none of these parameters are sufficient by themselves to detect fatigue, but should only be used in a supportive manner. As required by research question RQ1, the system was integrated into a typical car seat on a test system that allows the measurement of sitting and body characteristics. A study was conducted with six users of different body types. Using the data from the subjects, the processing models are tested and evaluated. By using the data from all subjects and randomly dividing them, a classification accuracy between 95% and 100% is achieved for the test group. However, leave-one-out validation shows that the models need a lot of data as the precision drops significantly. When evaluated on the entire data set with random partitioning, the nonlinear regressions worked quite well, but may be less suitable for subjects with certain body types. Based on the validation results where data of one participant was left out for testing, improvements still need to be made to the system. Fusion with other sensor devices already contributing to an assistance system could improve overall detection. In particular, parameters such as steering angle or pedal position could improve classification or detect situations that cannot be detected with capacitive proximity sensing alone. This data is already available in the vehicle's serial data system. The system could also be expanded to include other capacitive proximity sensors distributed throughout the vehicle. Sensors mounted under the floor mat or directly in the pedals could allow more accurate positioning of the lower limbs. The proposed prototype is still based on manual seat adjustment. An electrically adjustable car seat could be combined to automatically measure and adjust the driver. In addition to the performance of the processing models, the approach to data collection also needs to be improved. In particular, the exploratory study of this thesis needs to be extended to cover more body types and a higher number of users. It would be beneficial to identify a suitable set of training data that would allow the execution of a pre-trained system under real conditions. Thus, the system would need to be installed in a real car or a realistic simulator so that the functions can be tested in real driving situations. This should, of course, include car seats of different manufacturers and dimensions.

The next application we discuss in Chapter 4 is a capacitive proximity sensing enhanced child seat. Again, the capabilities of capacitive proximity sensing enable invisible integration into the child seat pan. Specifically, the sensing electrodes are placed under the non-conductive seat cushion. In addition, the system is autonomously embedded only in the child seat. Due to this setup, the subject is always closest to the sensing electrodes. Due to this condition, the system is not affected by objects between the subject and the sensing electrodes. This increases the robustness of the detection compared to systems that require a line of sight. Even when there is no object between the sensing electrodes and the person (with the exception of a child's seat cushion), changing temperature and humidity conditions affect the robustness of the system. Humidity can shield the object or at least change the offset of the sensors. Detection models that rely on static sensor data could be affected. Occupancy detection relies on static data. Therefore, wet cushions or changing temperatures could lead to incorrect predictions. Despite these limitations, a prototype was successfully created based on the design in Section 4.2. In addition, environmental measurement systems are installed in an ordinary vehicle to collect data for labeling and evaluation. With this setup, test runs are performed under real conditions. In these ten test runs, many variations of environmental conditions such as lighting and interior temperature are recorded. Due to being conducted in the summer, large ranges of interior temperatures are measured. Nevertheless, it would be beneficial for system evaluation if winter measurements or humidity simulations were also performed. Labels for head position detection are derived from the data of these test runs from the captured images. These images are

partially processed automatically. Thus, it should be noted that the labels themselves have measurement errors. Nevertheless, an acceptable performance is shown in the evaluation of the head position detection. A more robust labeling system could improve performance. Such labeling systems could consist of depth cameras or special motion markers. In addition to labeling, it should be noted that the test series was conducted with a minor subject. While the parents provided informed consent here, future tests could include diaper monitoring sensors. Thus, this could result in unfamiliar exposure to minors during testing. Therefore, an ethics committee would have to review this experiment. In summary, concepts for head position detection, heart rate detection, sleep state detection, and occupancy detection are defined. The built prototype is based on these concepts. An ordinary child seat is used. In this child seat all capacitive proximity sensors are included, so that an invisible integration into an autonomous system is possible. Nevertheless, system autonomy is only an idea so far. Concepts for an autonomous system must therefore be defined in the future. For communication, a cellular module could be built in. With the built prototype and additional sensors, data was collected in ten real test drives. With this data the defined concepts were trained and evaluated. Even though the environmental conditions vary within these test drives, more data needs to be collected from different subjects, different vehicles, and different child seats. This will refine the evaluation results. The project still does not cover all features in Figure 4.27. For example, detecting breathing rate and checking diaper condition is not considered in this project. In future research on the improved child seat, sensing electrodes could be integrated into the seat belt of the child seat, for example. These sensing electrodes in the seat belt could allow detection of breathing rate. Similar to heart rate detection, respiration rate detection is also considered important for a child seat monitoring system. Capacitive proximity sensing is already used for respiration rate monitoring in office furniture [BFW15]. Additionally, respiratory emissions like yawning are detected in Section 4.1. This feature therefore appears to be feasible in a child seat. To get the ground truth, a breathing rate monitoring system, such as a face mask, would need to be included in future measurements. It may sound strange, but a useful feature for a smart child seat would be diaper condition checking. This might lead to delicate topics, but information about diaper condition could help parents protect their children's skin and interpret the baby's articulations. To address this feature, measurements with diaper moisture sensors would need to be included in future measurements.

After both applications have been discussed, the specific contributions to the research question RQ1 can be examined and open questions can be identified. The concept is additionally applied to answer RQ1 in both applications. Thus, the components of the concept and how they can help address RQ1 under practical conditions can be explored. The research question is addressed by both applications. Existing vehicle structures are used and evaluation results are promising that capacitive proximity sensing can address problems in vehicles based on statistics and related research. Nevertheless, only application two has been tested under real driving conditions. Further evidence for research question RQ1 can be found when the systems are tested under real-world conditions. Additionally, the addressed issues show only a subset of the possibilities with capacitive proximity sensing. The emerging trend toward highly automated driving, in particular, may provide additional areas where information from capacitive proximity sensing can be useful in evaluating driving situations. Specifically, driver readiness for a takeover request could be improved by using capacitive proximity sensing to detect human emissions in automated driving. In general, any other application based on capacitive proximity sensing in vehicles can provide further insights for RQ1. This includes RQ2, where the domain is shifted from interfaces to vehicle-human interaction. Hence, the applications presented in Chapter 5 also contribute to RQ1. The concept of this thesis presented in Section 3.1, is considered suitable for the applications presented. Through the first step, analysis of existing systems, research and statistics, the applications that are developed with capacitive proximity sensors are put on a meaningful foundation so that real-world problems are addressed before the actual application is built. Thus, the applications developed demonstrate not only the capabilities of the capacitive proximity sensors, but also that these applications and the sensors are needed. The next step in the concept is to derive options or countermeasures for these real-world problems. Through this step, symptoms and indications and

thus human emissions can be identified. Human emissions are the entities that could be measured by capacitive proximity sensors. In particular, movements of the human body can be measured. The next step, knowledge of physical properties and applications in related work, is therefore critical if the required properties are to be developed with capacitive proximity sensors. The study of physical characteristics and related work in this step can also save time in developing processing models for capacitive proximity sensing data. Human emissions will then be linked to existing vehicle structures. This is another important step in answering research question RQ1. The selection of vehicle structures within range already gives an indication of a suitable sensor configuration that should be integrated. Furthermore, due to the distance between vehicle structure and human emission, the suitability of capacitive proximity sensing for specific human emission can also be tested. As required for benchmarking in the next step, a combination of resolution and detection range could also rule out capacitive proximity sensors. Benchmarking will test whether capacitive proximity sensors are best suited for the number of human emissions to be sensed. In Chapter 4, capacitive proximity sensing won the benchmarking when compared to cameras and ultrasonic sensors. Nevertheless, the benchmarking process seems to be already biased due to the previous steps of this concept. Features that should be enabled by capacitive proximity sensing have already been examined to see if this is possible with capacitive proximity sensing. Therefore, it is difficult to find any sensing system other than cameras that demonstrates the ability to measure human postures in a non-contact and unobtrusive manner. Ultrasonic sensors are further expected to be installed as an array of sensors around the driver so that multiple areas of the human body can be monitored, but other sensor systems could also enable certain functions of the applications. For example, heart rate detection could be enabled by an electrocardiograph system installed in the seat [Ple12]. If the specific problems are compared in isolation, several categories of sensors could win the benchmarking, resulting in a best system composed of several sensors. Sensor fusion in this case is not something that should be neglected during development. Some metrics of benchmarking are also considered to be susceptible to the taste of the developer. For example, a metric such as "unobtrusiveness" can have a strong impact on benchmarking if the developer feels that privacy and interior design implications are an important matter. The actual quantification of the benchmarking parameters could therefore be done in a customer survey. For example, in this thesis, unobtrusiveness in terms of privacy threats is considered important. Therefore, the analysis of privacy threats posed by in-vehicle systems is presented in Chapter 6. In the concept as shown in Section 3.1.9, several crucial steps for development are named. Several concepts for the development of recognition systems based on capacitive proximity sensors are presented in Chapter 4. Of great importance is the labeling of the acquired data. While data from for example cameras often provide the target itself, data from capacitive proximity sensors can hardly be labeled without additional information. Different labeling techniques were therefore demonstrated from both applications. Namely, data was labeled manually, using image processing, and using additional devices such as heart rate sensors or rotation rate sensors. The last step of the concept is the evaluation of the collected data. Strategies such as train-test-split, cross-validation, and leave-one-out validation can provide clues to the robustness and performance of the models found. In particular, the comparison between cross-validation at random and leave-one-out validation provides clues for further improvements of the models and data collection. If good performance is shown in cross-validation and poor performance in leave-one-out validation, this is an indication that more data from different subjects should be collected. Overall, the concept of this thesis leads to applications that sufficiently address research question RQ1 by showing how existing vehicle structures can be used to improve or replace human machine interfaces in vehicles with capacitive proximity sensing.

# 5. Providing vehicular human machine interaction using capacitive proximity sensing

We now shift the focus from interfaces without interaction to interfaces where interaction is based on capacitive proximity sensors. This directly addresses research question RQ2. To this end, the extended approach of this thesis, presented in Section 3.1.11, will be implemented in three applications. Each application will be developed, implemented in a prototype, and evaluated in user studies. A frequently used interaction option are gestures. The recognition of these gestures is investigated in two applications of Chapter 5. In contrast to symbolic gestures, which follow a predefined motion, pointing device-like interaction will also be provided. In addition to interaction capabilities, we will also discuss the effect of interaction that constitutes an application. For example, in an application, authentication of the user is enabled through interaction.

Authentication using gestures detected by capacitive proximity sensing is shown in Section 5.1. Section 5.1 is based on *AuthentiCap – A Touchless Vehicle Authentication and Personalization System* [FK17a]. A pointing device-like interaction based on capacitive proximity sensing is shown in Section 5.2. Section 5.2 is based on *HUDConCap – Automotive Head-Up Display Controlled with Capacitive Proximity Sensing* [FK17b]. Then, in Section 5.3, the focus switches from hand-based gesture recognition to the little-noticed foot-based interaction. Section 5.3 is based on *Robust driver foot tracking and foot gesture recognition using capacitive proximity sensing* [FK19] and *Enabling Driver Feet Gestures Using Capacitive Proximity Sensing* [FK18].

## 5.1. Tracking free air hand gestures for authentication

A mechanism for authentication in vehicles is provided as the first application in Chapter 5. In this application, human computer interaction in the vehicle is enabled only by using capacitive proximity sensors and existing vehicle structures. Research question RQ2 is thus directly addressed. Even though authentication mechanisms are generally not always based on interaction, interaction-based authentication offers potential for improving security and usability. The concepts from Section 3.1 and Section 3.2 are applied from idea to prototypical implementation. The first step is to review existing systems, research and statistics. This step is presented in Section 5.1.1. Issues related to these systems are also included in Section 5.1.1, so that the description of the system and the corresponding issues are discussed together. The countermeasures to those issues are the opportunities for a new system. Opportunities for a new system are presented in Section 5.1.2. Required indications and human emissions are then presented in Section 5.1.3. Whether those emissions can be captured using capacitive proximity sensing due to physical characteristics and related work is presented in Section 5.1.4. Once enough information on physical properties and related work is gathered, the decision of whether it is a feasible project with a vehicle structure in range and capacitive proximity sensing is considered the best sensing system is presented in Section 5.1.5. The technical development of the system, including the prototype, is then presented in Section 5.1.6. A built prototype is used to evaluate the system in Section 5.1.7.

### 5.1.1. Existing systems and their issues

Issues with existing systems can often be derived from accident statistics. The impact of driver distraction, on driving safety in 2018, was studied by the National Highway Traffic Safety Administration (NHTSA) [NHT20b]. As the report indicates, crashes due to distraction are often caused by drivers between the ages of 15 and 19. NHTSA gives examples of distraction, such as adjusting audio and climate controls or talking on a cell phone. In addition to distracted driving, a report from NHTSA [NHT20c], considering 2018 data, cites speeding as another leading cause of accidents. The largest proportion, of accidents caused by speeding, was caused by drivers between the ages of 15 and 20. 30% of fatal accidents caused by male drivers between 15 and 20 years old are due to speeding. 18% of fatal crashes are due to female drivers who are distracted. Although driving experience remains a prerequisite for safe driving, parents in particular do not want to expose their children to the risk of their self-inflicted risky driving behavior. To ensure that their children can still gain experience, driver authentication technology could help. Several options for authentication are mentioned by the NHTSA [LJS*10]. Voice recognition, facial recognition, eye scan and smart keys are mentioned as exemplary identification systems.

The solutions named by the NHTSA have already been implemented in real systems. A smart key system is provided by Ford [For21] that is called “MyKey”. The full capabilities of the vehicle are enabled when using the primary key. For secondary keys, the functions that may cause distraction or excessive speed are turned off. In addition, important safety systems can no longer be disabled. These include, for example, the speed warning system and the seat belt warning system. Secondary keys can be given to novice drivers. This solution is based on physical keys that can cause problems. Anyone in possession of the primary key has access to the full functions of the vehicle. If the solution is implemented as a keyless go system, further problems arise. An investigation into remote keyless entry systems for motor vehicles is shown by Garcia et al. [GOKP16]. This publication analyzes the vulnerability of various keyless entry systems. The automotive brands involved are VW Group, Alfa Romeo, Peugeot, Lancia, Renault and Ford. The vulnerability of millions of vehicles is revealed in their evaluation through the use of exploitation systems to defeat key-less go systems.

In addition to systems that rely on physical keys, other authentication systems rely on the integration of fingerprint sensors for at least a two-step identification system (fingerprint and key). In this case, driver personalization is enabled by the driver’s unique fingerprints. Nevertheless, this authentication mechanism has issues. One problem is the immutability of the biometric data, as mentioned by Bolle et al. [BCR02]. Passwords can be changed. However, it is very difficult to change biometric data (iris, ears, fingerprint, ...). Printed fingerprints or copies of the whole finger can trick such systems. Xia et al. [XLZ*16] has published an approach to detecting living fingers in a fingerprint scanner to counter this. The publication shows that the improvement of biometric identification is necessary, but not only fingerprints can be imitated. Face or ear recognition devices are being duped by masks. Cosmetic contact lenses are being developed to mimic iris features to trick iris recognition systems [BJ14]. In addition, fingerprint readers require contact between the finger and the sensor. Sensors must therefore be visibly mounted in the design of the vehicle interior, which may be unsuitable. In addition to fingerprint sensors, cameras are also used to recognize the driver’s face, for example. An example of such a system is shown by Min et al. [MCMD12]. In their design, a depth imaging camera is used to identify the user. Camera-based applications also have problems. A direct line of sight between the camera and the driver’s face is required so invisible integration into the vehicle structure is not possible. Capturing images of the driver’s face can also lead to privacy issues. An approach that does not require line-of-sight or visible design integration is being explored by Matthies et al. [MEM*19]. In their publication, an array of capacitive sensors is placed under elements on which the user can walk or stand, such as a doormat. Based on the characteristic profile of the user captured when subjects stand on the element, they are able to identify users with an impressive accuracy of 80% to 100% in a study of 15 participants. This publication is not automotive, but there are surfaces where this application could be used in a vehicle. Drivers have their feet on the floor of the vehicle when they enter a vehicle. This could enable a similar

detection mechanism if the sensor system is installed under the footwell cover. It would be interesting to analyze this condition in vehicles. So, the impact on interior design and privacy concerns could be addressed, but the data collected is based on biometrics. It is therefore difficult to change the authentication mechanism.

Unlock patterns are another authentication mechanism on touchscreens, as they are often used on cell phones. The user draws a pattern on the touchscreen to unlock the workspace. Unlike biometric data, the pattern is changeable. Nevertheless, the required contact between finger and touchscreen can become a problem. This authentication mechanism is being investigated by Sun et al. [SWZ14]. In their paper, the properties of different unlock patterns are analyzed. The limited pattern space leads to a limitation of security. Smudge attack or shoulder surfing are mentioned as possible security threats. In a smudge attack, the unlock pattern is detected based on the residue of the user's finger on the screen, as shown by Aviv et al. [AGM*10]. Directional light sources are used for this purpose.

### 5.1.2. Opportunities

Different authentication mechanisms were presented in Section 5.1.1. Each mechanism has specific problems. We now consider the options or countermeasures to address these issues. The authentication system should address problems of design intrusion, immutability of biometric data, and vulnerability to smudge attacks. Privacy issues, such as those encountered with cameras, should also be avoided. The capture of facial images in particular may interfere with regulations such as the European Union's General Data Protection Regulation [Cou16]. Data that threatens privacy, especially images of the face, should not be collected. Another issue that is presented in Section 5.1.1 is the design impact of visible systems. The influence on the interior design should be small. One opportunity is the use of sensors that can be invisibly integrated into the vehicle. Countermeasures to overcome the problems of biometric authentication are provided by changeable authentication mechanisms. Changeable authentication mechanisms such as touchscreen patterns have the problem that they can be recreated by fingerprints on the screen. Therefore, the opportunity here is to provide a system that does not rely on touch.

### 5.1.3. Symptoms, indications and human emissions

Several opportunities as countermeasures for issues of authentication systems were presented in Section 5.1.2. We now discuss possible interaction concepts that involve the countermeasures and thus follow Section 3.1.11. Section 5.1.2 concludes that the system should be contactless, based on changeable data for authentication, invisibly integrated into the vehicle, and facial images should not be collected. *Social awareness and skills* must additionally be considered when selecting interaction approaches for these countermeasures, as shown in Section 3.1.11. A natural way of interaction must be chosen, and the user must still be able to customize the authentication if needed. Few new commands should therefore be introduced by the system that need to be learned. Elements such as passwords are chosen as a changeable mechanism. In terms of interaction, a password can be articulated in different ways by the user. For example, a password could be spoken by the user. However, this interaction concept is neglected because the user's voice can be recorded and replayed, making the user's voice an immutable entity. Another opportunity is provided by a touch-less mechanism, as shown in Section 5.1.2. Contactless hand gestures are considered suitable. Many common gesture recognition systems are based on specific command sets that have to be learned by the user and therefore do not follow *social awareness and skills*. The user should therefore invent gestures himself so that system-defined gestures do not have to be learned. The gestures invented by the user still have to be recognized by the system. To summarize the emissions of this application, a sequence of gestures performed in the air should be recognized. Since these gestures are performed by hand, the position and velocity of the human hand is the emission considered.

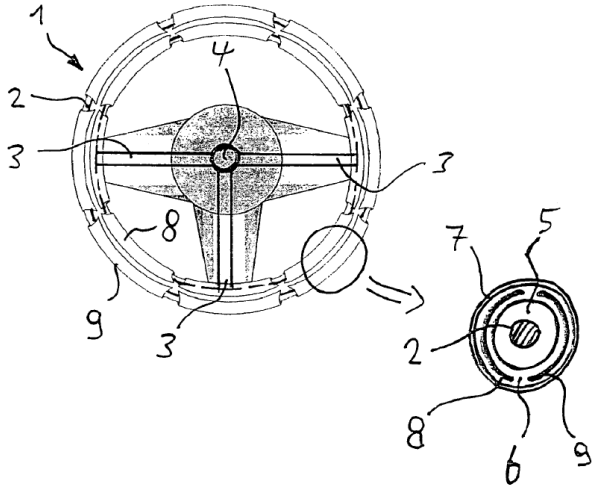



Figure 5.1.: Steering handle for motor vehicles and method for recording a physical parameter on a steering handle ( [RBL*08], Figure 1)

### 5.1.4. Physical characteristics and related work

Required human emissions for secure in-vehicle authentication were captured in Section 5.1.3. The emissions are the position and speed of the hand, which are now to be detected by capacitive proximity sensing. As shown in Section 2.1.2, the ability to detect changes in the position of the hand is provided by the use of capacitive proximity sensing. We now investigate an application from related research that tracks the position of the hand with capacitive proximity sensors to gather further evidence for the feasibility of this application using capacitive proximity sensing.

A steering wheel equipped with an array of capacitive proximity sensing electrodes to detect whether or not a hand is on the steering wheel is shown by Rieth et al. [RBL*08]. The patent drawing and the electrodes' topology are shown in Figure 5.1. The metal core of the steering wheel (No. 2), the electrodes (8,9) aligned in series with the outer ring, and the driver form a differential capacitor. The output of the measurement device is related to the contact between the hand and the steering wheel. The system can detect whether the hands are on the steering wheel or not based on capacitive proximity sensing. Even though contact is required in this system, the basic characteristic of tracking the position of the hand relative to the steering wheel is provided. Therefore, in addition to the physical characteristics, this system is used as the basis for the feasibility judgment in Section 5.1.5.

### 5.1.5. Feasibility, vehicle structure and benchmarking

An application that uses capacitive proximity sensing to detect the position of the hand on a steering wheel was presented in Section 5.1.4. Based on the physical properties of capacitive proximity sensing, it is assumed that the system functions can be realized during development. So, the verdict for feasibility is yes, based on the properties, this is a feasible problem with capacitive proximity sensing. The next step is to select a vehicle structure. The position of the hands should be detected by the system. A vehicle structure close to the hands is needed. Due to the position of the steering wheel directly reachable from the driver's view and the already existing steering wheel device with capacitive proximity sensing, in related work, the steering wheel of the

vehicle is selected as the vehicle structure. This also corresponds to the *body awareness and skills* entity of the interaction concept presented in 3.1.11, as steering wheels are designed to match the anthropometric conditions of the driver.

Since capacitive proximity sensors are now considered suitable for gesture recognition, the setup can be benchmarked against other sensors. The application and the weights for benchmarking must be defined according to Section 3.1.8. Hand gestures in the air should be made possible. Possible mounting positions near the hands, such as the inner roof and the steering wheel, are therefore selected. Based on the analysis of the natural positions of the driver's hands, the driver should use the hands in front of him. The maximum detection range for steering wheel mounted sensors is about 25cm [SAO79]. The minimum detection range is set to greater than 0 cm. This ensures that the hand does not make contact with the steering wheel. The detection range for roof-mounted devices is approximately 30 cm to 60 cm. If the detection range is larger, no further detection functions are enabled. Therefore, this weighting is set to low. The required resolution is set to less than 2 cm. The number of possible movements and the accuracy of gesture recognition will probably be correlated with the resolution. Therefore, the weighting for resolution is set to a medium value. The recording of hand movements is expected to be approximately real-time. It is expected that a refresh rate of 20 Hz is sufficient. Similar to resolution, it is assumed that robustness and gesture diversity correlate with the update rate. Therefore, the update rate is set to a medium value. Unobtrusiveness is important in terms of privacy and low design impact. The level of processing complexity remains a matter of investment. With respect to the prototypical stage of the application, the weighting of this metric is set to a low value. The system does not interfere with the functional safety of vehicles. Therefore, the metrics robustness, disturbance frequency, and calibration complexity are set low. The unique limitations criterion is derived from the system requirement. In this case, it is an exclusion criterion because the sensors must meet the requirements of non-contact, changeable authentication. Due to these statements, the weights of the application are $\vec{w} = (0.5\ 0.5\ 0.25\ 0.5\ 0.25\ 0.25\ 0.25\ 0.25\ 0)^T$.

Non-contact freehand gestures are to be made possible by the sensor technology. Capacitive proximity sensing and an exemplary camera [Ope20b] are therefore selected as sensor systems for benchmarking. The camera offers a resolution of 320x240 pixels at an update rate of 25 to 50 frames per second. A detection range larger than 35 cm is also possible. When capturing facial images, privacy may be compromised. In addition, a line of sight is required, so cameras cannot be integrated invisibly. As a result, the unobtrusiveness is set to a medium value. As stated in the camera description, algorithms such as face recognition are already included in the camera device. The processing overhead is therefore considered to be low. If the driver is not wearing a cap and his or her head does not cover the lens, cameras should be robust. A camera-based system can be disturbed by lighting conditions. In vehicles, lighting conditions are likely to change frequently. Camera systems should therefore be classified as rather low in terms of the disturbance frequency. Since the system has to deal with different skin color or gloves, the same rating is applied to the calibration complexity. Subsequently, the rating vector for the camera is $\vec{r} = (0.75\ 0.75\ 1.\ 0.5\ 0.75\ 0.5\ 0.25\ 0.25\ 0.5)^T$.

According to Puppendahl [GP15], the capacitive proximity sensing toolkit used achieves a resolution in the detection range of about 5 mm, at distances of 5 cm, to about 15 mm at 25 cm. An update rate of 25 Hz is given. Due to its physical characteristics, the system can be invisibly integrated into an existing vehicle structure. Facial images are not captured, indicating that features directly threatening privacy are not included. Unobtrusiveness is therefore rated the highest. The processing complexity is based on processing eight channels of acquisition, all of which are integer values. If a model can be found to derive the hand position from these values, the processing complexity should not be very high. The robustness is given with a medium value. The actual robustness depends on the processing. The sensors are not affected by lighting conditions, but capacitive proximity sensors can still be disturbed by changes in humidity, such as wet spots on the steering wheel. The rating for the disturbance frequency is therefore set to average. Finally, calibration complexity is the last metric. It also depends on the processing of the data. Processing as shown in Section 3.1.9 is considered to be little complex. Subsequently,

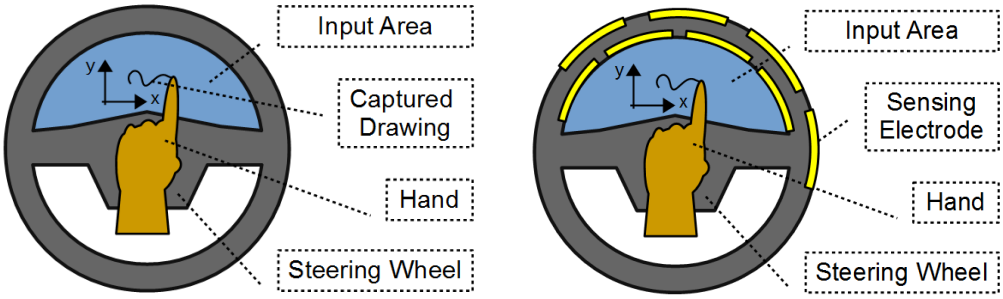



Figure 5.2.: Selected vehicle structure: steering wheel and sensing electrode position [FK17a]

the rating vector for capacitive proximity sensing is $\vec{r} = (0.75\ 0.5\ 0.5\ 1.\ 0.75\ 0.5\ 0.25\ 0.5\ 0.5)^T$. For the camera system, the benchmark score is 0.61 and for the capacitive proximity sensing system, the benchmark score is 0.64. Thus, the capacitive proximity sensors are selected as the benchmark winner for this system when mounted on a steering wheel.

### 5.1.6. Develop

Capacitive proximity sensors are considered the best sensing system when mounted on a steering wheel, compared to a camera mounted on the inner roof, as shown in Section 5.1.5. The next step is the development of the system. As shown in Section 3.1.9, there are several areas that need to be covered when developing a human machine interaction interface based on capacitive proximity sensing in a vehicle. These areas are the utilization of the vehicle structure in a prototype, data labeling, and data processing. They are being worked on in preparation for the evaluation of the application.

The steering wheel was selected as the vehicle structure to be equipped with capacitive proximity sensing. A sketch of a steering wheel is shown in Figure 5.2. Non-contact interaction is required. The inner steering wheel area is chosen as the input area. The area is labeled in Figure 5.2 (left: input Area). Due to the size of the input area, short words or patterns can be drawn by the user. Since the focus area is the free volume in the upper part of the steering wheel, this is enclosed by sensing electrodes. As shown in Figure 5.2, the sensing electrodes are placed at equal intervals on two semicircles on the steering wheel ring. The spokes and hub of the steering wheel are not covered with electrodes. The airbag deployment area is therefore not affected by the setup.

Now that the sensing topology is defined, the actual processing of the data can be determined. Hand tracking, in particular, is considered the basis for interaction in this application. The area for interaction is artificially limited, as shown in Figure 5.3. Due to this limitation, a start (within the detection range) and an end (outside the detection range) of the interaction can be easily detected. A relationship must be found between the output of the capacitive proximity sensors and the actual hand position within the steering wheel input range. In order to distinguish whether a gesture should be detected by the system, it must be distinguished by the system whether a driver hand or finger is inside or outside the drawing area. A material must be found as a basis for the sensing electrodes. The relationship between different materials and the measurement performance of capacitive proximity sensing is analyzed by Rus et al. [RSBK15]. Measurements with parallel aligned capacitive proximity sensing electrodes are shown in their publication. A nonlinear dependence between distance and sensor data is measured. Due to the nonlinear dependence and the fact that neither translation nor rotation of the driver's hand or finger is constrained, an attempt to deterministically find a correlation between position and capacitive proximity sensing data is skipped. A heuristic hand tracking procedure is used instead. To be precise, support vector regression

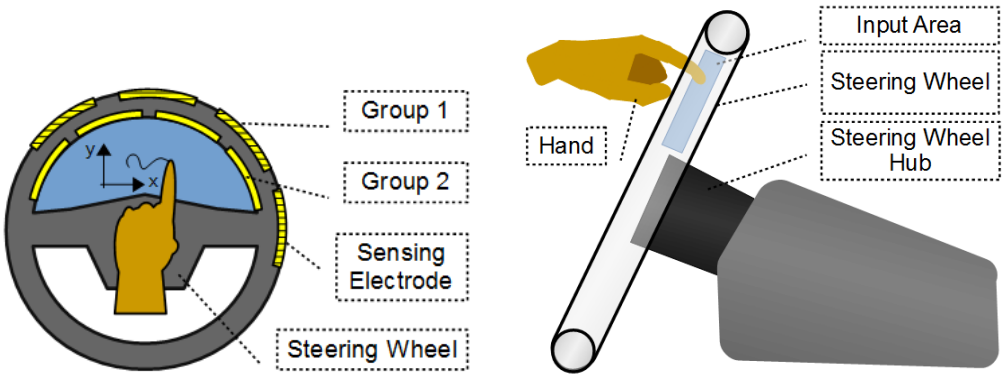



Figure 5.3.: Left: capacitive proximity sensing electrode grouping, right: Input area side view [FK17a]

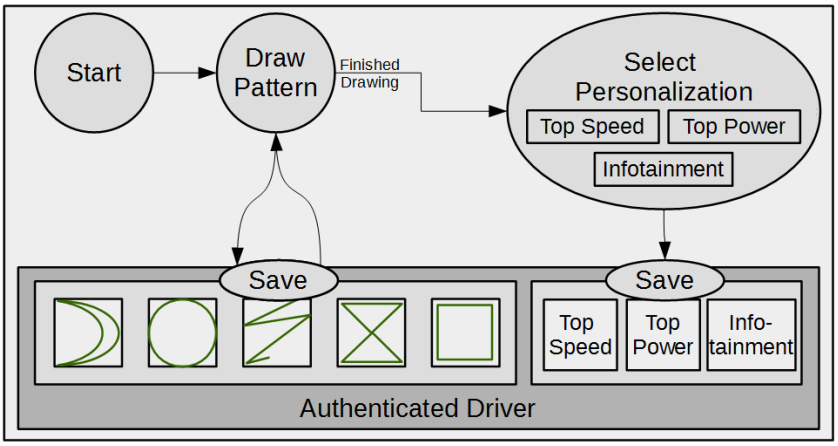



Figure 5.4.: Driver setup initialization process [FK17a]

models are used. In order to condition the data for the support vector regression model, appropriate preprocessing must be defined. Besides the nonlinearity caused by the physical properties of capacitive proximity sensing and the hand position, the measurement data is affected by environmental conditions. For example, the measurement is affected by temperature and humidity. All electrodes of the capacitive proximity sensors are in the same environment. To reduce the influence of these disturbance variables, the sensors are divided into two groups. Each group is shown in Figure 5.3. Each group is processed separately. The measured value of each individual electrode is related to the group of the respective electrode. The output value of the electrode is then divided by the sum of the group. Subsequently, the data is MinMax-scaled as shown in Section 3.1.9. Due to the expected similar changes in bias due to the confounding variables, the scaled output is considered invariant to the bias due to environmental changes. The output of this process is used as the input feature vector for two support vector regression models. Each output dimension $(x, y)$ is estimated by a separate support vector regression model. Another support vector machine classifier is used to detect whether the hand is within the detection range. In this case, the input feature vector consists of the MinMax scaled sensor values. The input area with a user hand in it is shown in Figure 5.3.

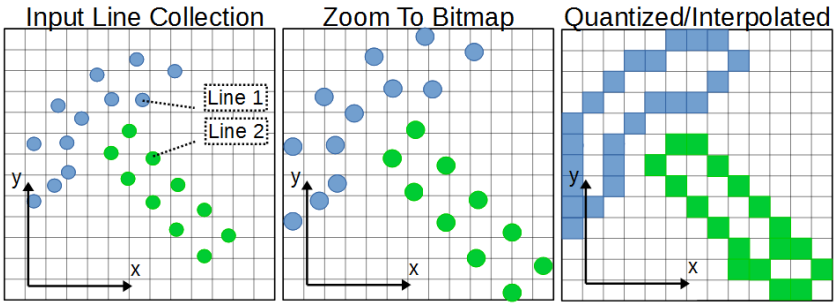



Figure 5.5.: Pattern acquisition [FK17a]

After the concept of hand tracking is defined, an authentication mechanism can be developed. Authentication is enabled by generic input patterns provided by the user, without restrictions on the form. Therefore, writing letters, short texts as well as inventing new patterns is not a problem for the user. The patterns can be combined to form passwords of different lengths. Nevertheless, this approach is limited by the user's ability to redraw their specified unlock pattern. The process for setting up authentication by the user is shown in Figure 5.4. After starting the authentication initialization, at least one pattern is drawn by the user. The pattern is then saved. More patterns can be added to the password until the password is considered strong enough by the user. The pattern drawn by the user is stored in a list. Then, vehicle conditions such as the maximum speed or infotainment settings of the vehicle can be restricted relative to the password. Both the personalization and unlock patterns form an authenticated driver entity. Subsequent attempts to start the vehicle must use this specific pattern for authentication. Once the driver is authenticated, the vehicle loads the stored driver unit. Due to the authentication process, multiple passwords can be set up by the driver for different situations. The feedback of the system which can address entity *Naïve Physics* of the interaction concept shown in Section 3.1.11 is not defined, yet. Based on the user's environmental awareness, he or she might expect a feedback from the vehicle if the authentication was successful. What is required is a response from the system that does not cause irritation to the user. When the user starts the vehicle, the infotainment system is usually activated. Therefore, if the user is authenticated, the system could start the infotainment system and greet the authenticated user.

After the concept for authentication is defined, patterns based on hand movements are selected as the basis for authentication. To capture these patterns from the hand movement and compare them with stored patterns, another process is defined. In this process, pattern acquisition is started when the user hand intersects with the input area. The first intersection is set as a reference point for further movements. As long as the user hand is in the input area, the position of the hand relative to the reference point is captured. The position is divided into $x$ and $y$ coordinates. The directions of the coordinates are shown in Figure 5.2. The time for drawing in the input area is not limited. When the user leaves the input area, a timer is started. As soon as a parameterized timeout is exceeded, the system saves the pattern drawn so far. If the timeout has not expired, the system waits for further input to be added to the current pattern. The collected sequences are scaled in $x$ and $y$ directions to ensure similar dimensions for all patterns. Then, the sequence points are converted to integer precision. Missing values between points are interpolated. An example is shown in Figure 5.5. An exemplary two-line input is shown in the first graphic of Figure 5.5. In graphic two, the lines are scaled until they match the bitmap boundary. In graphic three, the lines are quantized and interpolated. The final stored pattern can be seen in graphic three.

The pattern now generated must be processed so that future drawings of the driver can be compared with the previously stored pattern. To do this, the generated bitmap pattern is compiled into a single column vector. The generation of this vector of an example drawing is shown in Figure 5.6. It consists of four vectors that refer

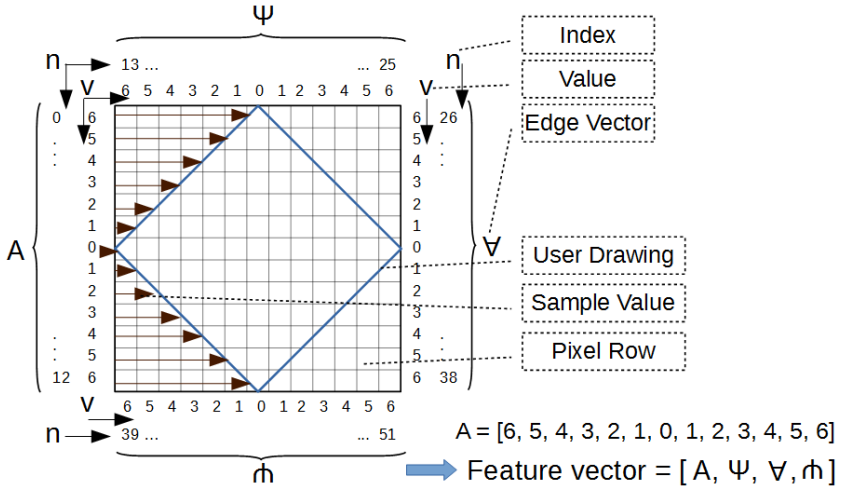



Figure 5.6.: User drawing feature extraction [FK17a]

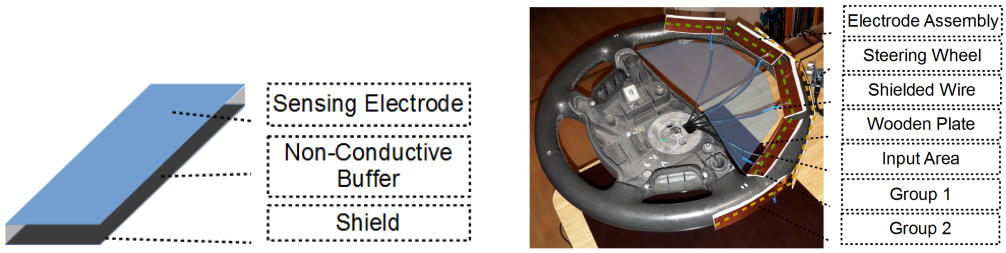



Figure 5.7.: Left: electrode setup, right: prototype assembly [FK17a]

to the number of pixels in an edge of the bitmap. The value of an element of the edge vector is the distance perpendicular to the edge to the first non-zero pixel of the pattern. The length of the column vector is obtained as four times the bitmap edge length. The considered dimension of the corresponding bitmap edge pixel position is represented by each index of the column vector. This feature extraction is based on the common OCR feature "distance profile" analyzed for example by Singh et al. [SKR15]. When the user wants to start the vehicle, she or he must enter the pattern. Each element of the drawing results in the column vector shown, which corresponds to the feature vector for an authentication classifier. Then, the newly drawn pattern is compared to the ordered patterns that were previously trained. Through this process, the identity of the user is verified by the system. To compare the feature vectors, the absolute deviation of each feature vector element is calculated. Then, the sum of the deviations is divided by the length of the feature vector. This yields the mean distance of the new feature vector ($x$) and the reference feature vector ($y$). If the mean distance is less than a given threshold ($t$), the pattern is detected as passed and the user must enter the next pattern. If the pattern is the last trained one of the pattern list, the user is authenticated.

Once the sensor topology layout and authentication mechanism are defined, the design can be integrated into a prototype. Eight capacitive proximity sensing channels and a sampling rate of 25 Hz are provided by the selected capacitive proximity sensing toolkit [GPBB*13]. Data transmission and power supply are included in

Figure 5.8.: Prototype with protective cover [FK17a]

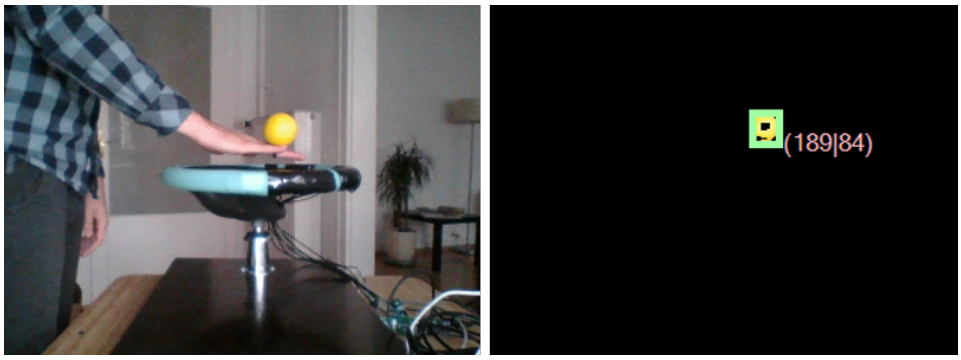



Figure 5.9.: Data labeling for hand position recognition

an USB connection to a test computer. The width of each electrode is set to 25 mm, while the selected length of all electrodes is 100 mm. Due to the shape of the steering wheel, a flexible electrode material is chosen. To be precise, a self-adhesive copper foil is used for all electrodes. The electrode structure is shown on the left in Figure 5.7. An electrode shield is used. A non-conductive buffer with a thickness of 0.5 mm is placed between the sensing electrode and the shield electrode. To minimize the influence of the sensor-electrode connection, the electrode and sensor are connected to the controller board with shielded wires.

These sensing electrodes and their respective shields are installed in an ordinary steering wheel of a production vehicle. The position of the electrodes and the steering wheel is shown on the right in Figure 5.7. The steering wheel is mounted on a base that is connected to a wooden plate. Non-conductive tape secures the electrode assembly to the steering wheel. Due to the ability to sense through non-conductive materials, the assembly is covered with a protective cover. Electrodes could also be integrated under the steering wheel casing. The final prototype is shown in Figure 5.8.

Using the prototype, data can hardly be labeled without additional sensors. The positions of the hand, in particular, cannot be derived from the data itself. A labeling mechanism is used to detect the actual position of the hand. The concept of the mechanism has already been presented in Section 3.1.9. A motion marker is used

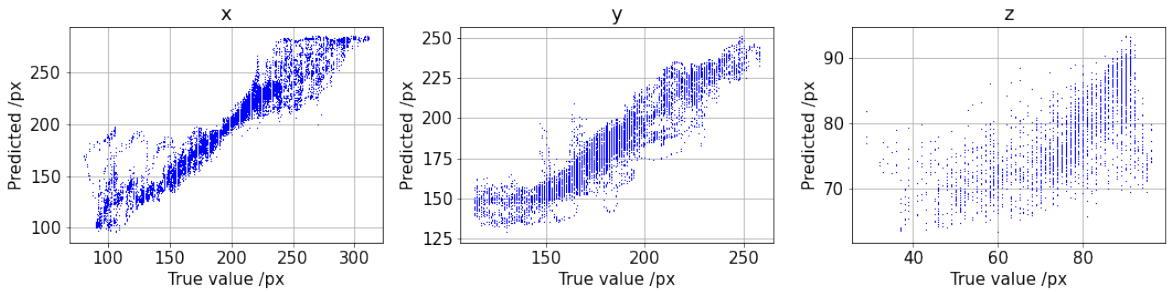



Figure 5.10.: Support vector regression results

| Dimension | $R^2$ | MAE | MSE |
|---|---|---|---|
| x | 0.90 | 9.89 | 247.64 |
| y | 0.87 | 7.96 | 120.12 |
| z | 0.45 | 6.67 | 101.86 |

Table 5.1.: Hand position recognition regression model results

to track the hand position. The motion marker is shown in Figure 5.9. This is a yellow ball that is attached to the hand. The image is filtered to the yellow color. Then the remaining objects in the image are enclosed by a rectangle with minimal area. The remaining object and the enclosing rectangle are shown on the right side of Figure 5.9. The concerned axis in Figure 5.9 is the $y$ axis with an exemplary current value of 189 pixels. So far, the individual patterns of the users do not have a label yet. Due to the concept, the labels are generated by the system itself. Therefore, no further processing is required here.

### 5.1.7. Evaluate

A basis for the evaluation is given by the prototype developed in Section 5.1.6. We will now evaluate the designed authentication mechanism based on the patterns drawn by the user. Before the driver can draw patterns, the position of the hand must first be detected. For this purpose, a model based on support vector regression was developed in Section 5.1.6. In particular, the planar position of the hand within the input area must be estimated using the model. The chosen model is trained with data collected with the prototype. 10,234 samples of labeled data for the $x$ axis, 8,882 labeled data for the $y$ axis, and 3,284 data for the $z$ axis were collected, even though the $z$ axis is not used for authentication. The predictions of the trained model and the true value of the axes are shown in Figure 5.10. Ten-fold cross-validation is performed to measure the performance of the regression model. The mean values of the cross-validation are shown in Table 5.1. The coefficient of determination $R^2$ is 0.9 for the $x$ axis, 0.87 for the $y$ axis, and 0.45 for the $z$ axis. Due to the good results of the support vector regression model for hand tracking, the model is used to capture arbitrarily drawn patterns. Several possible user input patterns captured by the prototype and the regression model are shown in Figure 5.11. Two exemplary patterns for symbols are shown in the first row in Figure 5.11. A stylized lightning bolt is represented by symbol 1.1 and a stylized ladder with one rung by symbol 1.2. Since the ladder consists of three lines, the hand also had to move out of the drawing area. Two letters are the next two characters. In detail, these are the letters “E” (2.1)

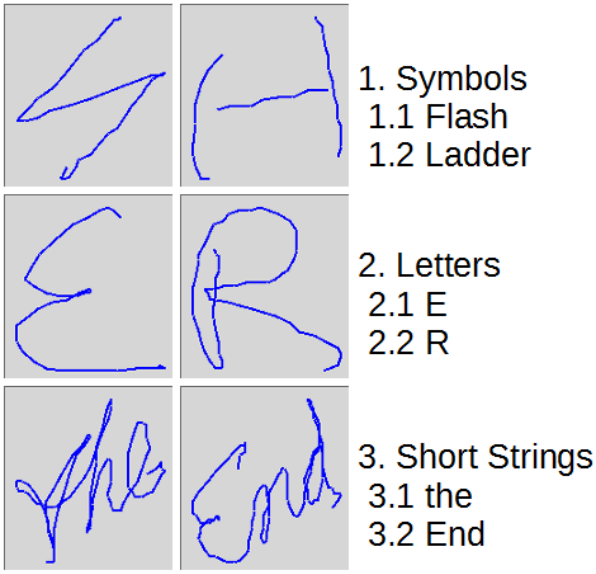



Figure 5.11.: Different user inputs [FK17a]

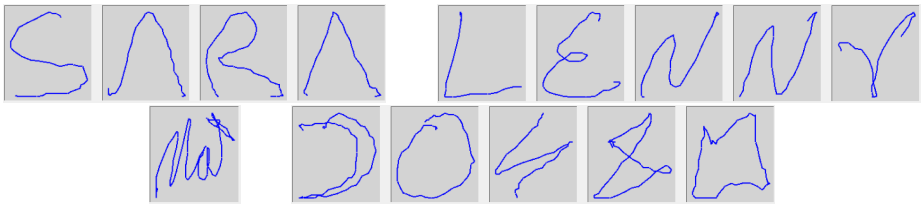


Figure 5.12.: From top left to bottom right: unlock patterns of Sara, Alexander, Matthias, and Sebastian. [FK17a]

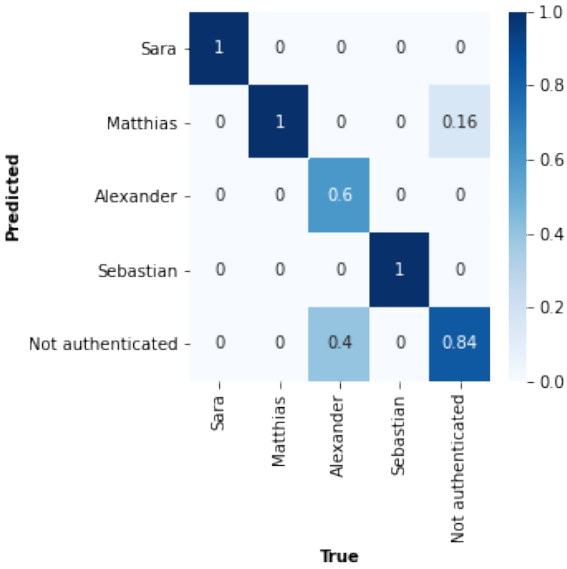



Figure 5.13.: Confusion matrix

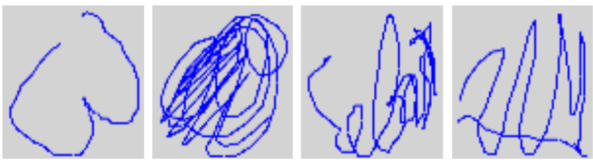


Figure 5.14.: False positive authentication: Matthias [FK17a]

and “R” (2.2). Short words are drawn in the last line of Figure 5.11. In particular, these are the words “the" (3.1) and “End" (3.3). The correlation between intended characters and recorded characters observed in Figure 5.11 is apparently sufficient. The coefficient of determination of 0.9 ($x$-axis) and 0.87 ($y$-axis) is therefore considered acceptable. The designed authentication mechanism is therefore simulated. Different users of the system with different input patterns are simulated. Four pattern sequences are tested in the authentication mechanism, the patterns are shown in Figure 5.12. The first unlock pattern is labeled Sara. It is a four-digit pattern and a mixture of symbols and letters. In particular, the pattern sequence consists of the letters “S” and “R” and twice the symbol “Arc”. The next pattern sequence is denoted by Alexander. Only characters are used in this pattern. In particular, the pattern sequence consists of the characters “L", “E”, “N", “N", “Y". Unlike the previous pattern, the pattern sequence denoted by Matthias consists of a short string of characters: “Mat" in italic font. It is a single pattern sequence. Finally, the last pattern is labeled Sebastian. Five symbols are used in this pattern: “moon”, “circle”, “lightning”, “sand clock”, and “square”.

These pattern sequences are used to test the basic function of the authentication mechanism. To evaluate the function of the system, the patterns had to be redrawn and recognized by the system as matching patterns. A first evaluation shows that if only one training pattern of the unlock pattern is provided to the system, it is hard to unlock afterwards. Redrawing the pattern Sara resulted in an error (false negative) in three attempts. Using the

| User | Pattern Sequence | | | | | Single Pattern | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Pass | Fail | Sum | Pass % | Fail % | Pass | Fail | Sum | Pass % | Fail % |
| A | 23 | 9 | 32 | 71.88 | 28.13 | 104 | 9 | 113 | 92.04 | 7.96 |
| B | 24 | 8 | 32 | 75.00 | 25.00 | 117 | 8 | 125 | 93.60 | 6.40 |
| C | 21 | 11 | 32 | 65.63 | 34.38 | 93 | 11 | 104 | 89.42 | 10.58 |
| D | 19 | 13 | 32 | 59.38 | 40.63 | 80 | 13 | 93 | 86.02 | 13.98 |
| E | 27 | 5 | 32 | 84.38 | 15.63 | 120 | 5 | 125 | 96.00 | 4.00 |
| Sum | 114 | 46 | 160 | 71.25 | 28.75 | 514 | 46 | 560 | 91.79 | 8.21 |

Table 5.2.: Table user study

Alexander pattern results in two false negatives in five attempts. The best result is achieved with the Sebastian pattern. The system could be accessed three times with the pattern. The worst performance is achieved with the pattern Matthias. Out of ten attempts, only three were successful. False positive decisions did not occur in this evaluation run. In summary, this test results in an overall true-positive rate of 12 out of 23 or 52%. Due to the low true positive rate, the authentication process is extended. More samples of the user patterns are now collected and added to the training samples. In particular, each pattern is redrawn three times for training. All three samples of patterns are now treated equally and all result in an authenticated driver if the user input deviation of all symbols is below the threshold (an average distance of 10 pixels). To test this small learning sample, each pattern is drawn five times. In addition, 25 incorrect patterns (label: not authenticated) are drawn to test for false positives. The normalized confusion matrix of this process is shown in Figure 5.13. A mean true-positive rate of about 89% is achieved. At the same time, a mean false positive rate of about 4% is obtained. The pattern Matthias is predicted in all false positives, although not authenticated is the true label. The Matthias pattern was difficult to repeat before the system received more training patterns, and leads to false positives afterwards. An example of four false positives for the Matthias pattern is shown in Figure 5.14. For pattern sequences with one pattern, more training patterns are therefore needed and combinations of relatively simple letters or characters lead to more secure authentication. For pattern sequences with more than four characters, the system's authentication mechanism seems promising. Nevertheless, the single-word pattern can be manually distinguished from the tested non-authenticated patterns. If we compare Figure 5.14 with Figure 5.12, the difference is obvious. Even though the authentication mechanism has several problems, it is assumed that the system is able to recognize redrawn pattern sequences.

After a suitable pattern capture mechanism is defined, the system can be tested with real subjects to prove its capabilities. A user study with five subjects is conducted with the prototype. All subjects have an age between 28 and 31 years. All subjects have a driver's license and four subjects own a car. In addition, the first registration date of these cars is between 2005 and 2014. Before the subjects are presented with the system, they are asked about their experience with capacitive proximity sensors. Experience is rated on a scale of one (no experience) to ten (high experience). Except for one subject with an experience of ten, all users indicate that their experience is below or equal to three. Users are then instructed on how to use the system. The pattern sequence labeled Sara is selected to be drawn multiple times by each user. The maximum number is 32, so since the pattern sequence consists of four individual patterns, each user had the chance to draw 128 patterns. If the user fails to draw a single pattern, the cycle for the sequence is terminated and the subject must start at the beginning of the next pattern sequence. Thus, the number of patterns drawn is reduced in this case. In addition to drawing the pattern sequence, several qualitative questions about the system are answered by the subjects. The first question is to evaluate the usability of the system by the subjects. The second question is whether the subjects think the


Figure 5.15.: Continental's augmented head-up display prototype with different driving situations [Abe16].

system can increase authentication security. The third question is whether subjects would use the system if it were available. The results of the task to draw the patterns for authentication are shown in Table 5.2. The user success rate for the entire sequence ranges from 65.63% to 84.38%. For the success rate of single pattern, the user success rate increases to 86.02% to 96%. The success rate of users can be compared with their respective experience. User E, who had the highest success rate of 96% for the individual patterns and 84.38% for the pattern sequence, reported an experience level of 10. User D had a success rate of 86.02% for single patterns and 59.38% for the pattern sequence. These are the lowest success rates. User D has the lowest capacitive proximity sensing experience level of one (no experience). No false positives occur in the experiment. All subjects believe that the system can increase security during authentication. All but one user would use the system if it were available. On a usability scale of 1 (difficult) to 10 (easy), the subjects rated the usability of the system as 5, 6, 7, 9, and 9. This means a medium to easy usability. At the end of the survey, subjects are asked to think of additional applications for the system. Most of the ideas relate to authentication systems. They say the system could be the unlocking mechanism of future desktops, safes or cell phones. So, the system's use might not be limited to steering wheels. One of the most frequently mentioned applications is unlocking a door. Another interesting application could be the connection of the system with signature-based cashless payment systems. In summary, the application is capable of providing a new type of interaction for authentication. It is based on an existing vehicle structure and uses only capacitive proximity sensing. Research question RQ2 is thus addressed and will be further investigated in Section 5.2.

## 5.2. A pointing device for head-up displays in vehicles

An in-vehicle human machine interaction system for authenticating users of a vehicle was developed in Section 5.1. Authentication is used before the vehicle can be started. We now use the steering wheel as a basis for a pointing device to control a head-up display in the vehicle. To develop this system, each step of Section 3.1.11 is passed through. Due to similarities with Section 5.1, several processing steps are referred to steps of Section 5.1. In general, we will see how an input device is developed to allow interaction between the driver and head-up displays to give the driver further control over the information displayed. In particular, a direct translation between the driver's hand movement into a computer mouse-like cursor will be provided. A proposal of head-up display icons/regions that the user can interact with on the display is considered an important application for head-up display control. The system not only competes in benchmarking, it is also compared in a user study with another input device: the touchpad.

### 5.2.1. Existing systems and their issues

Manually adjusting infotainment systems and looking at navigation is named by the National Highway Traffic Safety Administration (NHTSA) [NHT20b] as a cause of distraction. According to NHTSA, eight percent of all fatal crashes and 15 percent of injury crashes in 2018 were due to driver distraction. Head-up displays are being integrated into vehicles to address parts of this problem. Head-up displays allow drivers to keep their eyes on the road while reading vehicle information. Specifically, the driver's line of sight is enriched with more information on the windshield. The information displayed is not necessarily static. Recently, the displayed elements on the head-up display are adapted to the current driving situation. In addition, the development of head-up displays is moving from static 2-D displays to 3-D head-up displays. These systems are called augmented head-up displays. An exemplary augmented head-up display of Continental [Abe16] is shown in Figure 5.15. In Continental's system, the user is shown various sets of arrows representing the next navigation command. Vehicles ahead are highlighted in the head-up display, as are the current safety distance of the adaptive cruise control and the current route. The driver thus has to look less at the head-down display. The problem of driver distraction is thus partially countered with head-up displays, and head-up displays are being further developed to augment the environment. According to Feierle et al. [FBB19], the confidence of users in partially automated driving situations can be increased with head-up displays. Nevertheless, there are still problems with head-up displays. Only a few controls are designed to interact with head-up displays. For example, gesture control for head-up displays is being investigated by researchers such as Lagoo et al. [LCC*18]. In their paper, an infrared sensor-based system is installed in the interior to track the driver's hand movements and use them to control a head-up display with symbolic gestures. It makes sense to offer gesture control for head-up displays. As shown by Geiger [Gei03], haptic control is inferior to gesture interaction, in terms of speed and evaluation of system usability. Further head-up display control systems have emerged, as provided by Wang et al. [WCQ*19]. In contrast to Geiger, where infrared-based gesture recognition is used, symbolic gestures are recognized using RGB cameras in the system of Wang et al.. While gestures can facilitate the control of head-up displays, these systems have some drawbacks. One disadvantage of head-up displays could be the visual load for the driver. When too much information is displayed, according to Tufano [Tuf97], cognitive capture may be caused by head-up displays. The term cognitive capture means that when the driver is cognitively distracted, e.g., by the information presented in a head-up display, the driver is no longer monitoring the environment, even though the driver's eyes are focused on the road.

In addition to head-up displays, driver distraction is being addressed through the use of gestures to control infotainment in general. Gesture control is designed to ensure that drivers do not have to take their eyes off the road. Using gesture interaction can increase driving safety in the vehicle, as shown by Geiger [Gei03]. Gesture interaction in general can be done by using different sensor systems. For example, systems are based on infrared sensors or cameras. When cameras are used, it is possible for the driver's upper body to be recorded. The hands are included in this recording. Hand movements are then derived from the image sequence and interpreted as gestures, as described by Ashley [Ash14]. A line of sight is required for these systems. The line of sight, in particular, must be between the sensor system and the driver, or at least to an area with which the driver can interact. The systems must therefore be integrated into the visible interior design of the vehicle. This increases the effort required for the design of the interior. We will see in Chapter 6 that cameras, in the case of gesture control, record more data than necessary. If the entire upper body is monitored in particular, facial images could be captured, which could lead to privacy issues. The problems here are the line of sight that could be obscured and that privacy issues can be caused by imaging techniques.

In summary, one problem is that accidents are caused by distraction. This is being addressed in part through the use of head-up displays. Enhanced head-up displays extend the system so that more sophisticated information based on the environment can be displayed on the windshield. Current applications for controlling these head-up

displays focus on a series of symbolic gestures. Therefore, natural interaction can only be provided to a limited extent by current solutions. Data protection can also become an issue with gesture recognition when imaging technologies are used.

### 5.2.2. Opportunities

Various issues, statistics, and implementations of head-up displays and controls in automotive applications have been presented in Section 5.2.1. The opportunities we now consider to address these issues are similar to those in Section 5.1.2. Privacy can be better maintained without capturing facial images. If the system can be installed under existing vehicle structures, design impacts can be avoided. Another opportunity is to extend gesture interaction with head-up displays, for example with pointing gestures. The opportunity here is that natural interaction is possible with pointing gestures if deictic gestures of the user's hand can be captured with the system. This opportunity is supported if the context of what is being pointed at is present. In addition, an interaction method could be provided that reduces the cognitive and visual load and thus the risk of cognitive capture. Reducing the amount of information displayed in the head-up display is seen as an opportunity for a new system.

### 5.2.3. Symptoms, indications and human emissions

Symptoms, indications, and human emissions are similar to those in Section 5.1.3. The system is to be touchless so that free deictic gestures can be provided for natural interaction. The position of the hand must therefore be recognized. In this project, the hand is not used to form a pattern. Instead, the position of the hand is translated into a head-up display cursor. The user is able to point to entities in her or his environment, similar to the office application used by Bolt [Bol80]. Following the approach of pointing to objects, new commands are not introduced by deictic gestures. So, no new commands have to be learned by the user. The user must nevertheless be aware that the system exists. Hence, interaction framework point *social awareness and skills* is addressed.

### 5.2.4. Physical characteristics and related work

Indications required for hand tracking in vehicles were presented in Section 5.2.3. The position of the hand relative to the driver must be detected. Physical properties given by capacitive proximity sensors and thus enabling hand tracking are similar to those described in Section 5.1.4. Aside of hands on and off detection as shown in Figure 5.1, capacitive proximity sensing is used as pointing device in related works. Based on physical characteristics that are also provided in Section 2.1.2, several none-automotive applications are developed that track hand positions. The ability to track objects in free air using capacitive proximity sensing is shown by Aezinia et al. [AWB12]. Wimmer et al. [WHKS06] use four sensing electrodes to track hand position and gestures in front of medical displays so that the display is manipulated by the user without contact. Zeiss et al. [ZMB*14] use an array of capacitive proximity sensors to detect the hand position. In their project, gestures are derived from hand movements to open doors, for example. Basic hand position estimation outside the automotive domain using capacitive proximity sensors is also shown by Hobley [Hob12]. Similar to Section 5.1.4, enough applications and physical characteristics are available so that the feasibility of this project can be estimated in Section 5.2.5.

### 5.2.5. Feasibility, vehicle structure and benchmarking

Similar to Section 5.1.6, the driver must be able to operate the head-up display while driving. A structure is needed that is close to the driver's area of influence. This reduces the number of available vehicle structures. It

must also be possible for the driver to operate the application with her or his hands. It would be advantageous if the line of sight between the head-up display and the driver's hands would be in an area to increase operability and allow the user to look at her or his hands if necessary, to correct her or his hand position. Capacitive proximity sensors are already being used in automotive applications. One example is capacitive proximity sensors integrated into the steering wheel to detect hands-on/hands-off situations [RBL*08]. Since the steering wheel is encountered to be an appropriate structure for driver hand tracking in Section 5.1, the steering wheel is selected as the vehicle structure for this application. The entity *body awareness and skills* of the interaction concept in Section 3.1.11 is therefore also addressed. Based on the related work in Section 5.1.4 and the related work presented in this project, the application of capacitive proximity sensing is considered feasible for this project.

After the vehicle structure is selected and the general application is deemed feasible, capacitive proximity sensors are compared to other sensors to assess whether they are the best fit. The benchmark for the application is calculated similarly as in Section 3.1.9. The tracking of freehand movements is to be made possible. Therefore, the vehicle steering wheel and the interior roof are selected as possible positions for sensors. A detection range greater than zero and less than about 25 cm is selected for the steering wheel application and about 30 to 60 cm for devices mounted on the roof. Higher ranges do not improve the capabilities of the system. Therefore, the detection range is set to a low value. The required resolution is set to at least 2 cm and an update rate of 20 Hz should be sufficient. Unobtrusiveness is important in terms of privacy and low design impact. The weighting for processing complexity is set low. The metrics robustness, disturbance frequency and calibration complexity are set to medium. The criterion unique limitations is derived from the system requirement. In this case, it is an exclusion criterion because the sensors must function without contact. Based on these statements, the weights of the application are $\vec{w} = (0.5\ 0.5\ 0.25\ 0.5\ 0.25\ 0.25\ 0.25\ 0.25\ 0)^T$. Similar to the project in Section 5.1, free hand movements have to be detected by the sensor system. A camera mounted in the interior roof and capacitive proximity sensors mounted in the steering wheel are selected. A resolution of 320x240 pixels at an update rate of 25 to 50 frames per second is provided by an exemplary camera [Ope20b]. Resolution and update rate are therefore set to a good value. The detection range receives the best value. Due to the privacy and the eye-catching design, the rating for unobtrusiveness is set to a medium value. The processing complexity is set to a low value. Robustness is set to a medium value. The disturbance of the systems depends on the lighting conditions, which are likely to change, so the camera systems are rated rather low in terms of disturbance frequency. The same rating applies to the calibration complexity. The system must be able to handle different skin colors or gloves. Subsequently, the rating vector for the camera is $\vec{r_c} = (0.75\ 0.75\ 1.\ 0.5\ 0.75\ 0.5\ 0.25\ 0.25\ 0.5)^T$.

According to Puppendahl [GP15], the resolution within the detection range ranges from ≈5mm at distances of 5 cm to ≈15mm at 25cm. The capacitive proximity sensing system used has an update rate of 25 Hz. The system can be integrated invisibly into an existing vehicle structure without directly detecting privacy-threatening features. Therefore, unobtrusiveness is rated the highest. Processing complexity is based on processing eight acquisition channels, all of which output integer values. Whether a model can be found to infer the hand position from these values, the processing complexity should not be very high. The robustness is given with a medium value. The actual robustness depends on the processing. The sensors are not affected by different light conditions. Nevertheless, changes in humidity, such as wet spots on the steering wheel, can disturb the setup. Therefore, the rating for disturbance frequency is set to average. Finally, calibration complexity is the last metric. It also depends on the processing of the data. Processing as shown in Section 3.1.9 is regarded to be little complex. Subsequently, the rating vector for the capacitive proximity sensing system is $\vec{r_c} = (0.5\ 0.75\ 0.75\ 1.0\ 0.25\ 0.5\ 0.5\ 0.5)^T$. The benchmark score results in 0.61 for the camera system and 0.64 for the capacitive proximity sensing system. Thus, capacitive proximity sensors are the benchmark winner for this system if they are mounted on a steering wheel.


Figure 5.16.: Left: driving situation sample; right: same scene with information.

Figure 5.17.: Left: driving situation sample segmented. Middle: no information except user points on region of interest. Right: same scene with semi-transparent rectangles indicating regions of interest

### 5.2.6. Develop

Similar to Section 5.1, the steering wheel is selected as the basic vehicle structure. In fact, only a slightly modified design is used to enable a pointing device for head-up displays. Before the specific hand tracking algorithm can be designed, a concept for interacting with the head-up display is defined. In particular, the possibilities based on a cursor-like pointing device as a basis for interaction with an augmented head-up display are presented.

Further interaction possibilities in the head-up display should be made possible for the driver. Before the interaction space can be analyzed, it is necessary to identify what information should be shown in the head-up display. A head-up display should only show as much information as necessary to avoid cognitive overload. Only information requested by the driver should be displayed by the system. An exemplary driving scene was selected to illustrate the interaction idea. The driving situation is shown on the left side of Figure 5.16. Using the same scene, the right image of Figure 5.16 overlays information that relates to specific elements of the environment. *Naïve Physics* from Section 3.1.11 is addressed by this use of the environment as an interaction option. Interaction is based on specific areas of the driving environment represented by icons in the driving scene, shown as blue rectangles in Figure 5.16. For example, a blue rectangle in the sky area provides information about the weather at the destination, information about the next break opportunity is provided by a rectangle in the right forest area, the current distance setting of the adaptive cruise control is shown by a rectangle on the vehicle ahead, and information about the next food stop is indicated by a rectangle near restaurant or gas station signs. In order to determine the position of the interaction elements, the driving scene must first be segmented. Segmentation is provided, for example, by augmented head-up display systems from Continental [Abe16] or by the SegNet segmentation software (Cambridge University UK [KBC17]). The segmentation process is not part of this thesis, but must be considered because of the point *environment awareness and skills* in Section 3.1.11. All driving scenes in this project are manually segmented. The concept of interaction is based on two competing considerations:

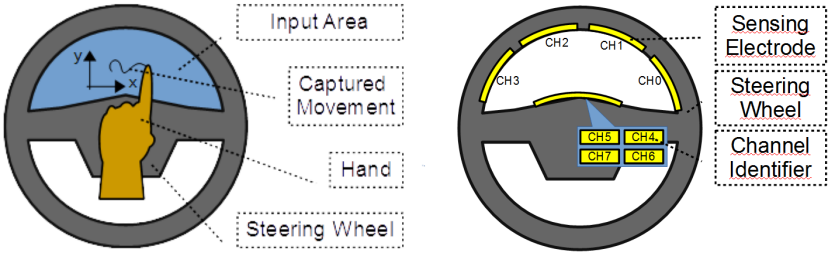



Figure 5.18.: Left: interaction area of the application; right: sensor topology [FK17b]

- Do not show any information at all and let the driver move the cursor of the application into an area, where he or she knows will get further information, like traffic run ahead.
- Place semi-transparent rectangles on the screen that indicate regions of information.

Both considerations are shown in Figure 5.17. The manually segmented driving scene is also shown on the left in Figure 5.17. Consideration one is shown in the middle image. The application's cursor is moved to the vehicle ahead to retrieve information about the current distance. The display of the information is triggered by the intersection of the cursor with the vehicle ahead in the segmented scene. Consideration two is shown on the right in Figure 5.17. In this case, all possible interaction objects are presented to the driver as semi-transparent rectangles. Again, the information is faded in when the cursor intersects with the segmented elements of the scene indicated by the rectangles. The idea of providing icons for interaction on the screen is preferred because it causes less irritation when the user points to places where no interaction is expected, but the system changes the appearance of the head-up display.

After a concept for the interaction has been found, a concept for the use of the vehicle structure can be defined. Even though the selected vehicle structure is the same as in Section 5.1.6, the topology of the sensors is changed to see if hand position detection can be improved with a new setup. The selected interaction area on the steering wheel is shown in Figure 5.18. A contactless, three-dimensional hand movement is provided. The detection of the movement is made possible by the fact that the interaction area is enclosed by capacitive proximity sensors. Individual channels of the measurement and thus the measurement electrodes are labeled "CHx", where x denotes a number from zero to seven. Electrodes CH0 to CH3 are located along the steering wheel ring in the direction of the input area. The electrodes CH4 to CH7 are arranged in a checkerboard fashion in the upper area of the steering wheel hub. The dimensions of the measuring electrodes of channels CH0 to CH3 are the same. The electrode dimensions of CH4 to CH7 are also the same.

After the sensor topology has been defined, a concept for a model for deriving the hand position from the sensor data can be defined. The sensing electrodes on the steering wheel are divided into two groups: steering wheel ring and steering wheel hub. The processing of the data, from sensor input to hand position, is shown in Figure 5.19. First, a median filter with a kernel size of three is applied. Then the data is MinMax scaled. The processed data is now in an interval from zero to one. As shown in Figure 5.19, the resulting data is split into two groups. The electrodes CH0 to CH3, on the steering wheel ring, are included in group one. The electrodes CH4 to CH7, on the steering wheel hub, are included in group two. Each scaled value of the electrodes is divided by the sum of the respective group. This gives a rate of the group for each channel. An example calculation for channel CH4 is shown in Equation 5.1. The MinMax scaled channel values are indicated by the index *scaled*.

$$CH4_{group} = \frac{CH4_{scaled}}{\sum_{i=4}^{7} CHi_{scaled}} \tag{5.1}$$

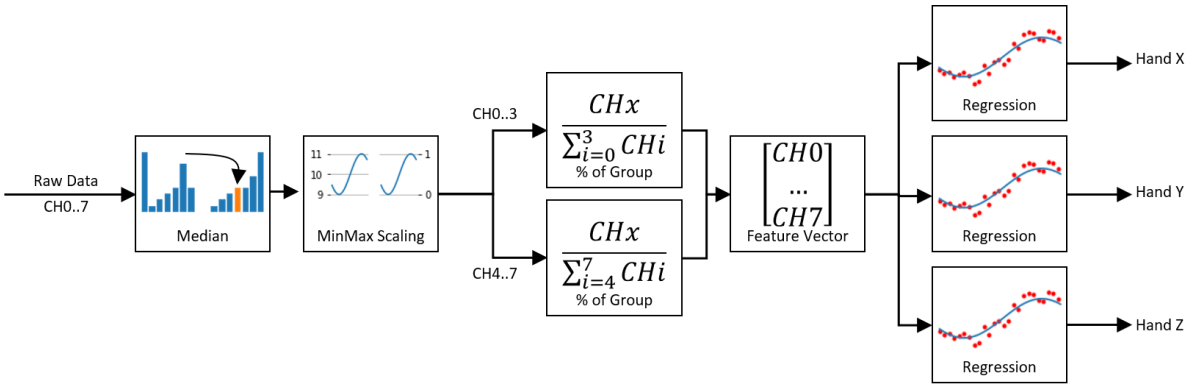



Figure 5.19.: Data processing flow, from data capture to head-up display cursor position

As shown in Figure 5.19, the position of the hands is predicted by three regression models. The feature vector for the multivariate regression models is comprised of $CH0_{group}$, $CH1_{group}$, ..., $CH7_{group}$. Each dimension of the hand position is estimated by a regression model. The $x$ and $y$ axes are shown in Figure 5.18. After the hand position is estimated, the detected $x$ and $y$ values are interpolated to the range limits of the head-up display to provide a cursor position on the head-up display.

Now we have defined the interaction concept and sensor topology, so that we can implement them in a prototype. The same steering wheel like in Section 5.1 is used for this project. The OpenCapSense toolkit [GPBB*13] is used as capacitive proximity sensing interface. The electrodes connected to the toolkit are made with the same dimensions and the same shielding and wiring configuration. Nevertheless, the sensing electrodes of the outer ring are moved so that they are located on the steering wheel hub. The new position is shown in Figure 5.18. As in Section 5.1, a camera is used to label the hand positions, in all three dimensions.

### 5.2.7. Evaluate

Now that we have built the interaction concept and prototype, the hand position estimator and interaction concept can be evaluated. Labeled training data must first be collected to evaluate and train the hand position estimator. Afterwards, the system is presented to several users. They have the possibility to use and rate the system. The users' ability to interact with the system is then compared to their performance with another interaction device.

In all data collected, the left hand was holding the left, lower area of the steering wheel. The right hand is always in the interaction area. The intensity of the left hand's grip is constantly varied during the measurement. Again, the data is collected and labeled as shown in Figure 5.9. 8,000 samples for each dimension are collected. As shown on the three diagrams in Figure 5.20, the data is collected by varying speed and magnitude of the hand. Both slow movements of the hands and fast back-and-forth movements are thus recorded. Each data point is processed according to Figure 5.19. To find the best model for the regression problem, five different models are trained. Results of the classifier evaluation are shown in Table 5.3. The selected classifiers are gaussian process, linear regression, a neural network with two hidden layers and 50 neurons each, a support vector machine model and a random forest regressor. Each regression model is validated using ten-fold cross-validation. Data for each axis are therefore randomly divided into ten packages, one of which is selected as the test set in each validation run, while the others are used for training. The mean values of the evaluation metrics for each cross-validation are presented. Abbreviations of the metrics are $R^2$: coefficient of determination, MAE: mean absolute error, and

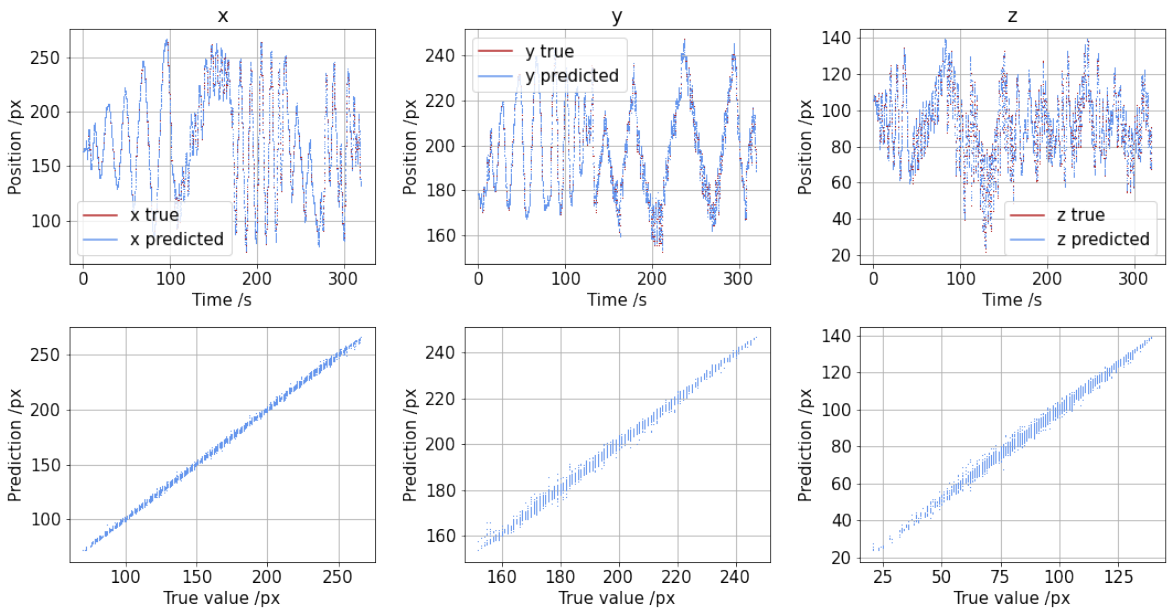



Figure 5.20.: True and predicted hand position

| Dimension | Regressor | $R^2$ | MAE | MSE |
|---|---|---|---|---|
| x | Gaussian process | 1.00 | 2.24 | 10.00 |
| x | Linear regression | 0.97 | 5.75 | 57.13 |
| x | Neural network (50, 50) | 0.98 | 4.50 | 35.51 |
| x | Support vector machine | 0.98 | 4.33 | 38.49 |
| **x** | **Random forest** | 1.00 | **2.03** | 9.04 |
| y | Gaussian process | 0.98 | 2.13 | 9.98 |
| y | Linear regression | 0.78 | 7.39 | 99.05 |
| y | Neural network (50, 50) | 0.90 | 5.08 | 45.22 |
| y | Support vector machine | 0.92 | 4.14 | 34.55 |
| **y** | **Random forest** | 0.98 | **1.88** | 8.73 |
| z | Gaussian process | 0.94 | 3.54 | 22.52 |
| z | Linear regression | 0.66 | 9.21 | 132.84 |
| z | Neural network (50, 50) | 0.88 | 5.34 | 47.72 |
| z | Support vector machine | 0.85 | 5.86 | 58.64 |
| **z** | **Random forest** | 0.96 | **2.84** | 16.94 |

Table 5.3.: Hand position recognition regression model results

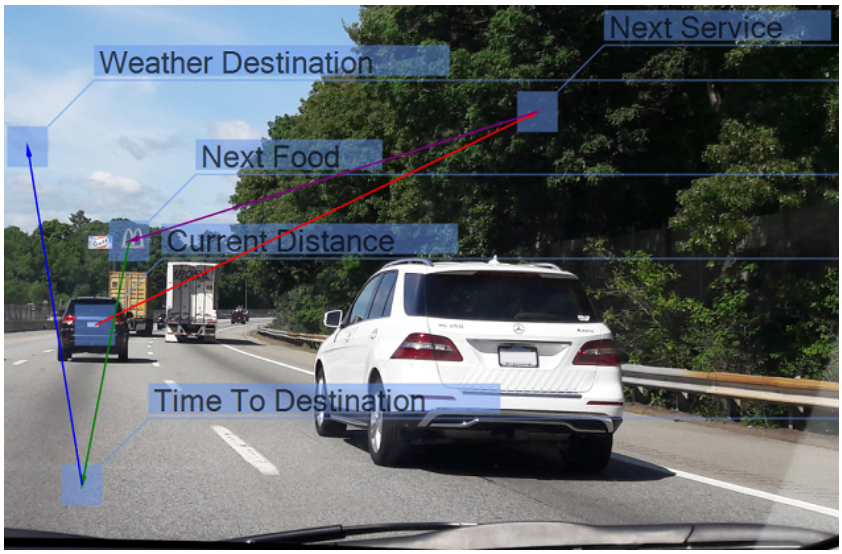



Figure 5.21.: Evaluation scenario driving situation, based on [FK17b]

MSE: mean squared error. For each dimension, the random forest model shows the best performance. Then, the whole dataset is used to train a random forest model. The predicted values and the true values for each dimension are shown in Figure 5.20.

Several pointing tasks on a static scene of a driving situation are performed by the subjects of the study. The exemplary driving situation is shown in Figure 5.21. A ride on the highway at moderate traffic is shown. The application icons *food*, *next service*, *adaptive cruise control safe distance*, *weather at destination place* and *time till destination reached* are included in the scene. The direct connection between the current symbol and the next target symbol for evaluation is represented by colored arrows pointing from symbol to symbol. The order of the arrows is red, purple, green and blue. In particular, the order of the icons that must be reached by the subjects follows this color sequence. Nevertheless, no arrows are provided to the subjects. When the user moves the cursor to the currently required icon, the next icon is highlighted. During the measurement, subjects were instructed to keep their left hand on the lower left side of the steering wheel. This instruction was sometimes ignored by the users during the evaluation. To allow a comparison between the proposed system and an existing ordinary pointing device, two scenarios are exercised by the users. In the first scenario, the proposed device based on capacitive proximity sensing is used. In the second scenario, an ordinary touchpad is used as the input device. In both scenarios, users had to move the cursor to specific points on the display. Scenario one is run five times. Scenario two is performed three times. This different number of repetitions is used because the proposed device and task are new to the subjects. Therefore, it is expected that the subjects' performance will increase from cycle to cycle. This procedure is chosen to test the users' acclimatization to the pointing devices.

The described procedure is carried out in a study with six subjects. Users are assigned a unique identifier from A to F. The pointing task is performed by each subject. A questionnaire is then distributed asking various questions about the usability of the system. In addition to the questionnaire on the subjective evaluation of the usability of different human machine interfaces, demographic data of the users are collected. All users own a driver's license and a car. Before we evaluate the information of the pointing task, the questionnaire results are presented. The questionnaire is answered by the subjects after they have performed the task with the pointing

| User | Experience | The Application | Touchpad | Difference |
|---|---|---|---|---|
| A | 8 | 8 | 5 | 3 |
| B | 1 | 3 | 5 | -2 |
| C | 2 | 8 | 8 | 0 |
| D | 9 | 8 | 9 | -1 |
| E | 1 | 5 | 7 | -2 |
| F | 1 | 7 | 8 | -1 |

Table 5.4.: Usability rating of the subjects concerning the application and the touchpad: 1 (low) to 10 (high)

| User | The Application | Touchpad | Difference |
|---|---|---|---|
| A | 10.28s | 5.69s | 4.59s |
| B | 5.06s | 3.61s | 1.45s |
| C | 4.9s | 4.04s | 0.85s |
| D | 4.54s | 2.95s | 1.58s |
| E | 3.53s | 2.72s | 0.8s |
| F | 4.21s | 4.66s | -0.45s |

Table 5.5.: Interactive head-up display performance of the test user's minimum time consumption in seconds

device. The users are asked to rate the usability of the proposed system and touchpad on a scale of 1 to 10, where 1 means not usable and 10 indicates high usability. They are asked about their experience with capacitive proximity sensing. The same scale is used here. Regarding the experience with capacitive proximity sensing, four users rated their experience as less than or equal to 2 (Value 1: users B, E, F; Value 2: User C). Users A and D are experienced in using capacitive proximity sensors. An experience level of eight is chosen by User A and nine by User D. A computer mouse, keyboard and touchscreen are used daily by all subjects. With the exception of User A, a touchpad is used daily by all subjects. Since touchpads are present in our performance test, the subjects were also asked to rate the usability of the cursor task with touchpad. The subjects' usability ratings for both systems are shown in Table 5.4. Since usability is a subjective estimation, the difference in usability between the proposed application and touchpads is calculated with usability(application)-usability(touchpad). A better usability of touchpads is indicated by a negative difference value. The usability of the application is rated better than that of the touchpad by User A. For User C, both systems show equal usability. The usability of the proposed application is rated one point worse than that of the touchpad by users D and F. The usability of the proposed application is rated two points worse than that of the touchpad by users B and E. Then, the users are asked if they think the proposed application is useful. This is answered in the affirmative by all users. Furthermore, a technically mature system would be used by the test subjects on a daily basis. Additionally, users are asked if they think the system can reduce distraction while driving. Four users agreed, while users B and E were not sure about this.

We now consider performance of the subjects in using the system. Each subject is given an introduction to the system. The screen visible to the subjects is shown in Figure 5.22. The subject's cursor is displayed as a red square and the next target icon as a purple square. Each subject is instructed to reach the next icon on the head-up display as quickly as possible. The red square is thus moved by the subjects to the purple square as quickly as possible. This instruction applies to both applications, the touchpad and the proposed device based on capacitive


Figure 5.22.: Pointing task sample screen at data capture

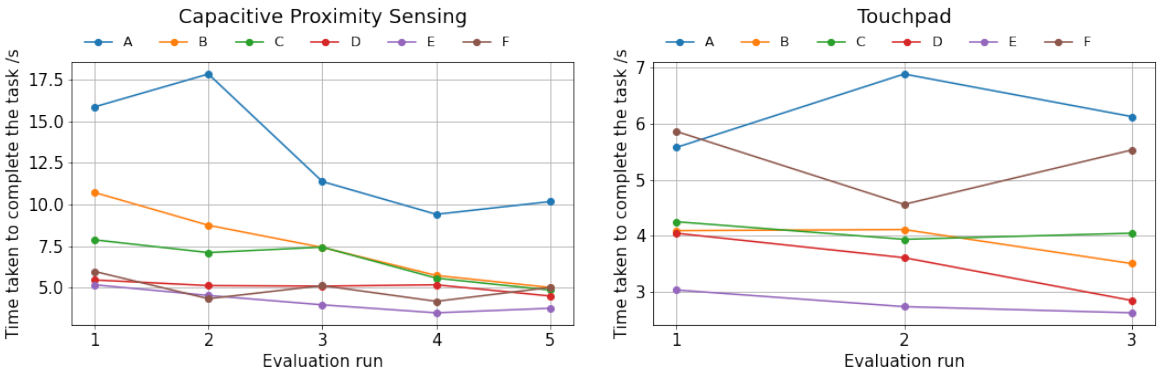



Figure 5.23.: Time taken by the subjects to complete the task

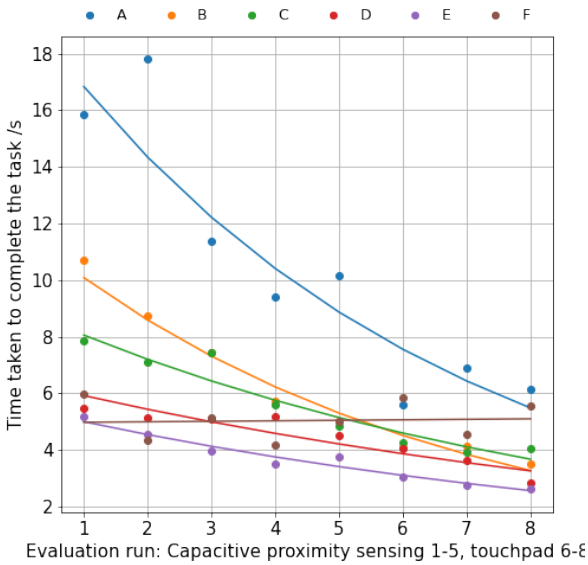



Figure 5.24.: Combined evaluation runs

proximity sensing. During the evaluation, the time taken by the subjects to complete the task is measured. The time required by the users in both tests can then be compared. A visualization of the required time in all cycles for both scenarios is shown in Figure 5.23. In particular, the performance of the subjects using the proposed device is shown on the left of Figure 5.23. Performance of the subjects using the touchpad is shown on the right of Figure 5.23. As shown on the left of Figure 5.23, the time required decreases from cycle one to five. The biggest progress is shown by User A. The time consumption is reduced by 7.66 seconds. User B's time consumption is reduced by 5.69 seconds, User C's by 3.1, User D's by 0.96 seconds, User E's by 1.68 seconds, and User F's by 1.8 seconds. A minimum time consumption of 10.28 seconds by User A, 5.06 by User B, 4.9 seconds by User C, 4.54 seconds by User D, 3.53 seconds by User E, and 4.21 seconds by User F is achieved. In addition to the performance of users with the capacitive proximity sensing-based device, the performance of users with a touchpad is shown in Table 5.5. Users achieve a minimum task completion time between 2.72 seconds and 4.11 seconds using the touchpad. With the exception of User F, the time consumption of all users is better when using the touchpad compared to their performance with the device based on capacitive proximity sensors. User A's performance is improved by 4.59 seconds when using a touchpad. A performance difference of about 1.5 seconds is shown for users B and D and about 0.8 seconds for users C and E. Since the users performed the same driving situation in both cases, the performance increase could be caused by learning the driving situation. The touchpad tests are performed after using the capacitive proximity sensing-based device. A joint plot for both devices is shown in Figure 5.24. Exponential trend lines are added to the data points. The coefficient of determination is calculated for each trend line. A coefficient of determination greater than 0.9 is calculated for users B, C and E. A coefficient of determination of approximately 0.85 is calculated for users A and D. The coefficient of determination for User F is only 0.4%. With the exception of User F, a decreasing task processing time can be seen in all trend lines. To further compare the touchpad and the application, the evaluation records the course of the users' interaction with both devices within the driving situation. The best performance in terms


Figure 5.25.: Interactive head-up display performance test. From top to bottom: User A to F, left: the application, right: touchpad. [FK17b]

| Level | Name | Steering Acceleration Deceleration | Driving Environment Monitoring | Dynamic Driving Task Fallback Performance | System Driving Modes |
|---|---|---|---|---|---|
| *Driver* monitors the driving environment | | | | | |
| 0 | No Automation | Driver | Driver | Driver | n/a |
| 1 | Driver Assistance | Driver and system | Driver | Driver | Limited |
| 2 | Partial Automation | System | Driver | Driver | Limited |
| *Automated driving system* ("System") monitors the driving environment | | | | | |
| 3 | Conditional Automation | System | System | Driver | Limited |
| 4 | High Automation | System | System | System | Limited |
| 5 | Full Automation | System | System | System | Unlimited |

Figure 5.26.: Levels of automated driving [SAE18]

of task completion time is shown in Figure 5.25. The direct lines between the symbols are displayed in the same color as the user's pointing curve. The current direction of the task is indicated by arrows.

We now conclude Section 5.2 to move on to another interaction system of this thesis. We now have a set of two interaction applications based on the steering wheel vehicle structure. Both applications are based on hand interaction. Thus, the diversity is limited to the application ideas that can be controlled by the hands. Nevertheless, this project extends interaction from purely symbolic gestures to explore deictic gestures in vehicles. However, hands are not the focus in Section 5.3. We have finished Section 5.2 rather quickly, but will discuss the topic of interaction for head-up displays again at the end of this chapter.

## 5.3. Enabling new ways of interaction in vehicles

Sections 5.1 and 5.2 addressed hand-based gesture recognition as an interaction option. Hand-based gesture recognition is widely used. Recognition of these gestures is already used by a large number of vehicle manufacturers such as Volkswagen [Vol] or BMW [BMW]. Little research exists on foot gestures, especially not in vehicles, but drivers' feet are one of the first extremities to be idle while driving, e.g., through cruise control. This is also evident in the development of automated driving, whose levels of automation are shown in Figure 5.26. The elements of driving used by the feet are already automated from level 2 [SAE18]. The driver's feet could be used for more tasks than just operating the pedals, such as human machine interaction. We now consider a process that provides the utility of the driver's feet for interaction in the vehicle. For this project, we again follow the concept of this thesis from Section 3.1.11.

### 5.3.1. Existing systems and their issues

We begin by reviewing current issues and related work to gather evidence on what opportunities exist to address these issues with an interaction system based on the driver's feet. A National Highway Traffic Safety Administration (NHTSA)) [NHT20b] statistic already used in Section 5.2.1 is also used here as the basis for issues. NHTSA describes that driver distraction is causal in eight percent of all fatal crashes, in 2018. Distraction is caused, for example, when the infotainment system has to be operated with buttons or touchscreens that require the driver

to look in the direction of the controls. Gesture recognition is seen as a way to counteract this problem. Gesture recognition is often based on hand gestures. The driver's feet are often neglected in this consideration, even though they are often inactive while driving. The literature also contains little research on foot-based gestures in vehicles. Nevertheless, foot gestures are also used by applications outside the automotive domain. So, the problems addressed by these applications may also be present in vehicular applications. Similar like other recognition applications [YK13, YK10], several ways to track feet outside of vehicle applications provide applications that focus on features such as foot shape. An exemplary system is presented by Scott et al. [SDYT10]. The fact that whole-body movements are implied by foot gestures due to kinematic linkages is used in their publication. By using an accelerometer located at the hip, foot gestures are detected. Specifically, a cell phone accelerometer located in the back pocket of the pants is used to detect body movements. Based on the captured data, ten different foot gestures can be distinguished. In particular, the features are caused by the rotation around the heel and the toe. Therefore, these ten gestures are composed of rotation and tapping gestures. The recognition model is based on a naïve Bayes classifier. Collected data from six subjects in the study are used to evaluate the model and an impressive accuracy ranging from about 82% to about 92% is achieved with respect to the different gestures. If this system were to be used in the automotive domain, several problems arise due to the kinematic linkages and the fact that the driver does not always have her or his cell phone in her or his pocket. Kinematic linking could be disabled in seated scenarios. The driver is usually sitting on the car seat, so that this approach may not be applicable in vehicles. They state that gesture-like acceleration patterns could be induced by activities such as walking without gestural interaction. Nevertheless, the system could provide interaction for disabled people who are unable to perform hand-based gestures. This condition may be present in vehicles. A system that is not based on hand interaction could provide gesture control for disabled people. In particular, if the control is not tied to the driver's seat, so that other passengers could also interact with the system.

A further approach for the detection of feet gestures outside the vehicle is presented by Fukahori et al. [FSI15]. In their publication, the gesture-dependent pressure distribution between the feet and the floor is monitored by pressure sensors. Although one might think that this could be captured with pressure sensors placed under the floor, the pressure sensors are actually contained in the user's socks. Thus, the system function is possible when using ordinary floors without further instrumentation. A potential use case is also described in the publication: The system can be used in crowded public spaces such as streetcars, where people cannot even use their arms or hands. Gestures are performed by the user shifting her or his foot pressure from the toes to the heel or root side. An evaluation of the system is performed, which includes a multimedia application that is controlled with the feet. The effect of the gestures is placed in the current context of the application, so that the set of gestures is related to the current state of the application. Depending on the state, the number of gestures recognized by the system ranges from two, such as answer call or ignore call, to five gestures in browser navigation, map navigation, or media player control. The application is tested in a study with five subjects, where gesture recognition shows an average accuracy of 91.3%. Even though this is an impressive accuracy, further evaluation shows that the performance of the system is highly user-dependent. Matthies [Mat18, pp. 140–150] is working in a similar area. Instead of using socks with pressure sensors, he uses capacitive sensors embedded in the sole of the shoe. This setup enables him to distinguish between foot gestures, recognize body postures and walking styles of a user. For example, by shifting pressure areas on the sole, the user can control avatars in virtual environments. The system is tested in these environments, for example, when playing video games. Wearing pressure-sensitive socks or shoes with modified soles while driving could be applicable, so that the proposed systems could also be used in vehicles. In this case, there is the problem that the driver would have to wear special, probably expensive additional equipment that may wear out. Due to the required contact between the feet and the ground, this could impede the selection of free air gestures and limited an ergonomic usage in vehicles.

We now consider another system in which foot gestures in the vehicle, using cameras, are studied. Due to the use of a camera, Tran et al. [TDT12] can predict the movement of the feet towards the pedals. The driver's

intention of which pedal to use can therefore be predicted by the system. For this purpose, a hidden Markov model is used for prediction. The features for the model are generated by evaluating the optical flow of the recorded image sequences. After development, the system is tested in a study with twelve participants. In different tasks, pedals are actuated by the subjects. Seven pedal actuation states are distinguished by the system: neutral, i.e., no actuation, brake actuated, brake released, moving toward brake, accelerator pedal actuated, moving toward accelerator pedal, and accelerator pedal released. In the evaluation, the mean correct classification rate is 93.77%. During the evaluation, a "leave-one-participant-out" validation is performed. In this validation, the accuracy of the classifier decreases. By early prediction, the intended pedal use of the driver can be estimated 133ms before the actual pedal foot contact with a true positive rate of 74%. Although the results are impressive, the system has issues that should be addressed in this project. Line of sight is required when using cameras. Therefore, the sensor system must be visibly integrated into the vehicle interior design. This will make each camera visible to the user. Privacy issues are expected to be less relevant, as it is unlikely that facial images will be captured by a camera pointed at the pedals. Nevertheless, they are listed for the sake of completeness. This system is furthermore used for monitoring, so that no intended interaction is necessary.

### 5.3.2. Opportunities

We have looked at various issues and systems, so that we can now turn to the opportunities that address these issues. From the statistics considered, it is generally evident that distracted driving is a significant risk. This distraction can arise when the driver must turn his or her focus from the roadway to buttons for controlling multimedia. The use of gestures is one way to address this problem. Hand gestures are used in many gesture recognition devices. Disabled people may not be able to perform these gestures. Foot gestures could help address this issue. The question of how a system can recognize foot gestures prompts further research in this area. The foot tracking devices presented, which are used outside the vehicle area, are not suitable for in-car tracking. Moreover, the system should not be based on additional systems that must be carried by the driver. In addition, systems based on pressure sensors limit possible interaction to foot-to-ground contact. One opportunity is to use a sensor system that can detect spatial movements of the feet, such as cameras. Camera-based sensors have some limitations. They require a line of sight and therefore cause visible design impacts. Because of their ability to capture more information than needed, they can also cause privacy issues. The opportunity here is to choose a sensor system that can measure through non-conductive material and record only needed information. If such a system is selected, it can be integrated into existing vehicle structures with no visible design impact.

### 5.3.3. Symptoms, indications and human emissions

We have identified various opportunities and thus requirements for a system to be developed, in Section 5.3.2. We are looking for a way to recognize foot gestures that can also be performed in the air. Based on the concept from Section 3.1.11, we will now select a set of foot gestures that address the point *social awareness and skills* in particular. Existing gesture sets are therefore investigated to define or find a suitable set for foot gestures. In particular, natural human gestures and gestures in human vehicle interaction may differ from each other in terms of recognized motion and intention. In the following, different types of gestures and the difficulties associated with them are shown. Then we will select gestures from them and discuss their properties.

In general, the desired system stimulation by gestures is achieved by correct gesture execution. For some gestures, predefined movements must be remembered by the driver. The cognitive load on the user when remembering these gestures depends on the gesture types. An exemplary gesture type overview is provided by Hummel et al. [HSO98]. One type is symbolic gestures, five of which are shown as examples in Figure 5.27. This gesture type is related to the recognition capability of the system. Symbolic gestures like pinch-to-zoom,


Figure 5.27.: Examples of symbolic gestures [HSO98]

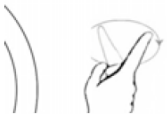
| Gesture | Freehand G. | Micro G. |
|---|---|---|
| **Play/ Pause** An open palm with fingers spread for playing/ pausing the music. |  |  |
| **Next/Previous** A swipe gesture to the switch to the next/ previous song. |  |  |
| **Louder/Softer** A clockwise/ counterclockwise circle gesture to control the volume. |  |  |

Figure 5.28.: Häuslschmid et al. gesture set [HMB15]

for example, are offered by many touchscreens. Pinch-to-zoom is shown on the right in Figure 5.27. As stated by Cassell [Cas98], these kinds of gestures are not intuitive to the user and have to be learned, similar to a programming language. Another type of gesture is the gesticulation of people when they speak. Speech recognition would have to be included in such systems for interaction to capture the context of the gestures, as shown by Hummel et al. [HSO98]. In addition to symbolic gestures and gestures during conversation, there are act gestures, such as those shown by Francis et al. [Que94]. In this gesture, for example, the shape of the object could be formed with the user's hands, or the position of the object could be indicated by gestures performed by the user. Contextual information such as the location of the object must therefore be known to the applications that work with these gestures.

A more technical approach is taken by Häuslschmid et al. [HMB15]. In their research work, an investigation is conducted on freehand and micro gestures. Both types of gestures and their application concepts are shown in Figure 5.28. Freehand means that the user has no contact with a surface while performing gestures. A hand rest is provided for the gesture-guiding hand while the subject performs microgestures. Both types of gestures are used, for example, to control the multimedia system in a car. The gesture types are compared in a study with 24 participants. In this study, gestures and driving maneuvers are performed simultaneously by the participants. An advantage for microgestures is shown in the results of the study for tasks involving lane changes while driving. Nonetheless, gesture completion is found to be a problem for microgestures. This suggests higher driving confidence for microgestures and higher gesture completion success for freehand gestures.

Until now, we have analyzed gestures based on hand movements. In this project, the focus is on foot gestures. The results of related work related to hand gestures must be projected onto foot gestures. Based on the results of

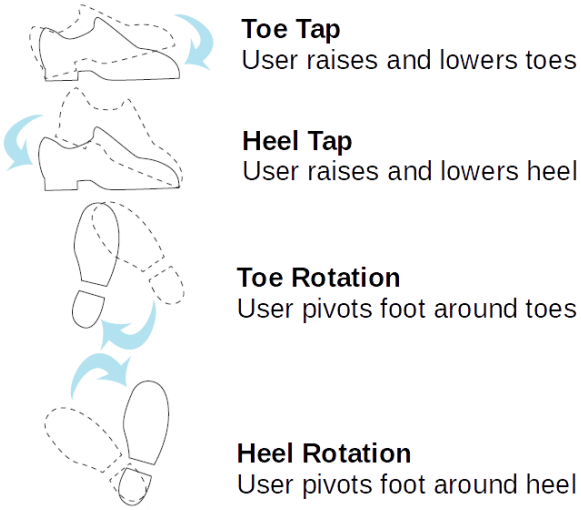



Figure 5.29.: Selected foot gestures [VSA*15]

Häeuslschmid et al., foot gestures with a fixed pivot point are used because the pivot point is considered similar to the hand rest. In addition, the driver's muscles could become fatigued if the foot has to be held up. If there is a fixed point, concerns about the driver's ability to perform these gestures frequently are reduced. Act gestures or gesticulating while speaking are preferred in this review of gestures by Hummel et al.. In general, better user acceptance is given by natural human gestures. These gestures are context-dependent. Due to the limitation of foot gestures and the restriction to use gestures fixed in one point, these gestures are intended for specific applications. Foot gestures must therefore be included in these applications to allow natural interaction while driving. Another point to consider when selecting gestures is the number of gestures. While a fast and specific system control is provided by a large number of gestures, it is shown by Kern et al. [KS09] that the cognitive load on the driver increases with the number of control interfaces. A small set of gestures is therefore chosen for this project.

The gestures are selected from a summary of foot gestures published by Velloso et al. [VSA*15]. In this summary, eleven different foot gestures are examined, which are composed of specific movements such as rotation, tapping, swiping, and movements with both feet. Seven of these gestures require a fixed point for execution. Since this project is a first investigation of foot gestures, we do not use gestures that need to be executed with two feet at the same time. This reduces the gesture set to five gestures, of which the shake gesture is again excluded, since its execution is expected to cause fatigue in the driver's foot. In the end, four gestures remain: Toe Tap, Heel Tap, Toe Rotation and Heel Rotation. These four gestures are shown in Figure 5.29. In summary, the remaining set of gestures requires the driver's single-axis coordination ability. Thus, each gesture consists of a single degree of freedom. For example, a rotation around the heel, with the toes moving up and down, is required for the Toe Tap gesture. A rotation around the toes is required for the gesture Heel Tap. Although each gesture is performed with only one foot at a time, driving situations in which the driver's feet are not involved are addressed by this project. Such driving situations include driving with cruise control or automated driving situations. Thus, each selected gesture can be performed with both the left and the right foot. Now that the gestures have been selected, the human emissions caused by the execution of these gestures can be summarized. The presence of the

driver's feet must be detected by the system. The gestures refer to pivoting movements of the foot. Therefore, movements such as rotation or translation of the foot must be detected by the system.

### 5.3.4. Physical characteristics and related work

We now have a set of selected foot gestures to which we have now identified the human emissions. The emission to be measured is the movement of the foot. We are now gathering information on whether these emissions could be measured with capacitive proximity sensors. We collect this information for further preparation of Section 5.3.4.

The main physical characteristics of capacitive proximity sensing are presented in Section 2.1.2. Following these properties, capacitive proximity sensors can sense through non-conductive material. Therefore, there are no problems due to non-conductive covers of the vehicle foot space. Nevertheless, the material of the shoes could vary from person to person. Conductive material could be present in the shoes. The conductive material, however, is carried along with the driver's foot. So, foot tracking with capacitive proximity sensors is possible even if the shoes are made of conductive material. It is expected, however, that different shoe materials will affect the strength of the sensing output. Nonetheless, the ability to detect the position of the human foot is presented in several publications. In particular, a system that detects feet is presented by Siegmund et al. [SDF*18]. The system is based on capacitive sensors. These sensors are used to detect the foot position of people in transit areas. If a person tries to illegally follow an authorized person, this is detected. A similar application is shown by Braun et al. [BHW12]. In their system, capacitive proximity sensing is used to locate people in a living room, for example. All publications rely on the presence of feet on the floor.

### 5.3.5. Feasibility, vehicle structure and benchmarking

Due to the findings in Section 5.3.4, the verdict on the feasibility of this system is set to yes, it appears feasible that capacitive proximity sensors could detect driver foot gestures when installed in the vehicle. This is also supported by the physical properties of the sensor system, which are already being used in non-automotive applications, as shown in publications by Braun et al. [BHW12] and Siegmund et al. [SDF*18]. A suitable vehicle structure can thus be selected for mounting the sensors. Since driver-initiated foot gestures are to be detected by the system, a vehicle structure near the driver's feet is chosen as the basis for mounting the electrodes. The driver's feet are located in the legroom, which is enclosed by the pedals, side walls, floor, and driver's seat. The driver's feet are in contact with the floor, especially when the gestures are reduced to contact with the floor. Therefore, the floor of the legroom is chosen as a vehicle structure for mounting sensing electrodes. The side walls of the footwell are included as a mount for the sensing electrodes. It is expected that the performance of foot sensing will increase if the sensing electrodes are mounted in the side walls. The footwell of a vehicle is usually covered with a non-conductive textile or other synthetic material. Sensing electrodes can therefore be placed invisibly under the covering material.

Now that we have analyzed the feasibility and found a suitable vehicle structure for mounting the sensors, we will compare the system with other sensors in a benchmark process. As already shown, possible positions close to the driver's feet are given by the surrounding elements such as the floor of the pedal area, the roof of the pedal area or the side walls. Since the feet can move within the legroom, the detection range of a sensor, when installed above the feet, is less than 50 cm. When the sensors are mounted on the floor of the legroom, less than 25 cm of detection area is required to monitor the position of the feet. The required resolution is set to at least 2 cm. Since the speed of actual gesture execution is unknown, an update rate of 20 Hz is chosen to capture motion in near real time. The next metric in the benchmarking, unobtrusiveness, is considered less important if the sensor

is mounted in the roof of the leg room. In this case, only images of the feet could be captured by a camera. The impact on the design could be negligible since the driver cannot see the roof of the leg compartment. The weighting for the processing complexity measure is set to a rather low value since this project aims to develop a prototype for a proof of concept. It is not known whether functional safety would be compromised by a system malfunction. Nevertheless, a non-safety-relevant application is expected. For this reason, the metrics robustness, disturbance frequency and calibration frequency are set to medium. The criterion unique limitations is derived from the system requirement. In this case, it is an exclusion criterion because free air gestures and thus free air motion must be detected when the system is mounted on the legroom roof. If the system is mounted on the floor of the legroom, it is unclear whether gestures can be detected using only touch-based sensors. The detection range weight is therefore set to a low value. Due to these statements, the weights of the application are $\vec{w} = (0.5\ 0.5\ 0.25\ 0.25\ 0.25\ 0.25\ 0.25\ 0.25\ 0)^T$.

Capacitive proximity sensing, pressure sensors and an exemplary camera [Ope20b] are selected as sensors. The camera provides a resolution of 320x240 pixels with an update rate of 25 to 50 frames per second. Resolution and update rate are therefore set to good. A detection range of more than 50 cm is given. Images containing more information than needed can be captured by cameras. Privacy interference is indicated. Cameras cannot be integrated invisibly. The unobtrusiveness is therefore set to medium. Processing complexity is set to low. If the driver is not wearing a skirt, foot tracking is considered robust. The interference of the system depends on the lighting conditions, which are likely to change. Therefore, camera systems tend to be rated low in terms of disturbance frequency. The same rating applies to the calibration complexity, as different shoe sizes, shapes and colors have to be detected. Subsequently, the rating vector for the camera is set to $\vec{r} = (0.75\ 0.75\ 1.\ 0.5\ 0.75\ 0.25\ 0.25\ 0.25\ 0.5)^T$.

According to Puppendahl [GP15], the resolution of capacitive proximity sensing in the detection range goes from approx. 5 mm at 5 cm distance to approx. 15 mm at 25 cm. This is sufficient when the sensors are mounted under the floor of the footwell. Therefore, the resolution is set to good. An update rate of 25 Hz is given. The system can be integrated invisibly into an existing vehicle structure without directly detecting privacy-threatening features. Unobtrusiveness is rated best. The processing complexity is based on processing eight acquisition channels, all of which are integer values. If a model can be found to derive the foot position from these values, the processing complexity should not be very high. The robustness is given with a medium value. The actual robustness depends on the processing. The sensors are not affected by different light conditions. Nevertheless, changes in humidity, such as wet spots on the floor, can disturb the setup. Therefore, the rating for the disturbance frequency is set to low. Calibration complexity is the last metric. It also depends on the processing of the data. Processing as shown in Section 3.1.9 is considered of low complexity. Subsequently, the rating vector for the capacitive proximity sensing system is $\vec{r} = (0.75\ 0.5\ 0.5\ 1.\ 0.75\ 0.5\ 0.25\ 0.5\ 0.5)^T$.

An array of pressure sensors placed under the floor of the footwell is the third sensor system considered. To derive the metrics for this sensor system, the publication of Meyer et al. [MAST10] is set as basis for information. In their publication, an array of pressure sensors is created. In this project, it is expected that these sensors can be integrated under the leg space of the vehicle. According to the publication, the resolution is set rather low at 3x3 cm. The update rate is about 90 Hz. So, the update rate of the measurement is set high. Only contact can be detected. Therefore, the detection range is set to a very low value. Similar to capacitive proximity sensing, these sensors can be integrated invisibly. This is why the unobtrusiveness is set to a maximum value. The processing complexity is unknown. Since these sensors can only measure contact while the majority of the object is occluded during gestures, it is set to a poor value. It is expected to be difficult to disturb these sensors. Therefore, the robustness and the disturbance frequency are set to a good value. The calibration complexity is set to a very low value. Since the sensors can only measure the contact between the foot and the ground, it is expected to be difficult to distinguish gestures if the driver uses different heel shapes. Similarly, the unique limitations are set to a low value because these sensors can only detect objects when there is contact between the

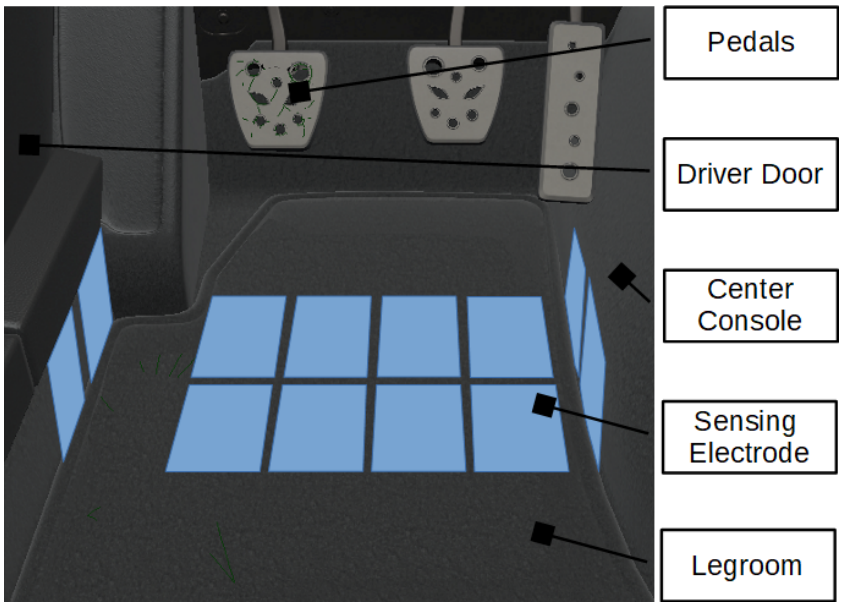



Figure 5.30.: Driver legroom with sensors and electrode topology [FK19]

sensor and the object. Subsequently, the rating vector for pressure sensors mounted on the legroom floor is set to $\vec{r} = (0.25\ 1.\ 0.\ 1.\ 0.25\ 0.75\ 0.75\ 0.\ 0.\ )^T$. This results in a score of 0.6 for the camera system, 0.6 for the capacitive proximity sensing system and 0.53 for the pressure sensor system. Thus, the camera and the capacitive proximity sensing solution are the winners of this benchmark. Nevertheless, each parameter of the benchmarking process is based on assumptions and similar systems. Changing one measure could likely change the outcome of this process.

### 5.3.6. Develop

The legroom floor and side walls are selected as vehicle structures for the system in Section 5.3.5. A set of gestures which should be detected is presented in Section 5.3.3. We are now focusing on developing a concept for the instrumentation of the vehicle structure and a suitable processing of the capacitive proximity sensing data to detect these gestures. The position of the foot is not restricted in the leg space. Gestures can be performed by the driver in all degrees of freedom, so rotation and translation in all three directions are included in the motion of the feet. Therefore, this unconstrained spatial condition is covered by a three-dimensional capacitive proximity sensing electrode array topology. The designed topology is shown in Figure 5.30. Since the gestures are limited to one pivot point, so that the driver does not have to keep her or his leg up all the time, the gestures are partially performed with contact of the foot with the floor of the footwell. The driver's feet are therefore in close proximity to the sensing electrodes when they are included as shown in Figure 5.30. To ensure invisible integration without affecting the interior design, each sensor can be mounted under textile covers. The considered coordinate system within the legroom is shown in Figure 5.31.

Before working on the gesture recognition concept, we discuss possible applications of foot gesture recognition in vehicles. The meaning of foot gestures must therefore be analyzed and compared with other interaction

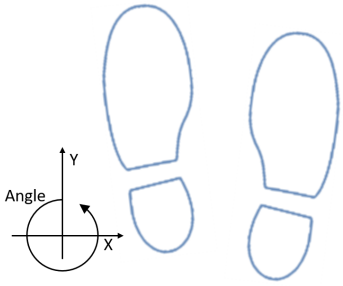



Figure 5.31.: Legroom coordinates

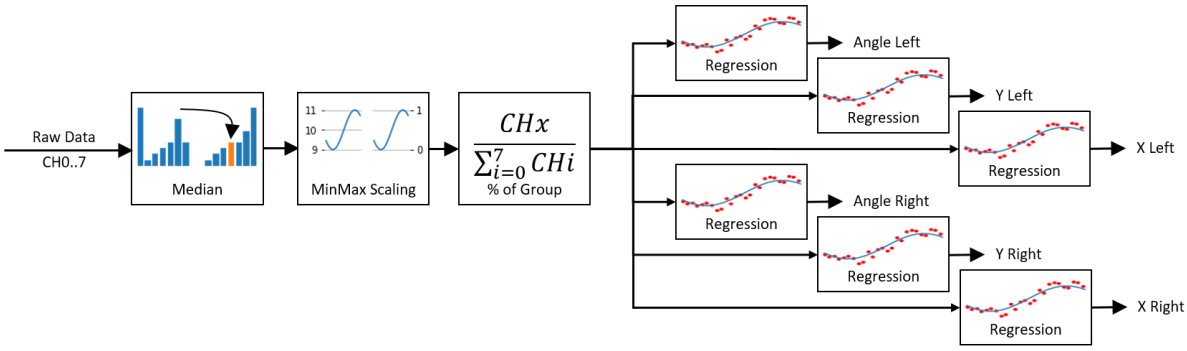



Figure 5.32.: Position prediction model

applications and natural interaction. For example, the Heel Rotation and Tap Rotation gestures could be compared to swipe gestures on touchscreens. A multimedia system could respond to Heel Rotation or Toe Rotation similarly to swipe gestures. These gestures could therefore be used to switch between two states, for example in a playlist in the media control. Tapping gestures could be related to acknowledging dialogs or selecting music tracks. Depending on the human memory capacity to recall these gestures, these four gestures could be used for non-natural motion-related control. In this case, users would have to learn the gesture function depending on the system. As for natural interaction, people do not normally use their feet to point at objects. Moreover, they do not draw object shapes with their feet during communication. According to Nierenberg et al. [NC71], feet movement during communication is usually implicit. Emotions can be signaled by people with their feet. For example, the Heel Tap gesture could be performed by a bored person. A person holding back strong emotions might lock her or his ankles. A method for emotion detection based on capacitive proximity sensing is already being investigated by Rus et al. [RJBK18]. In their paper, furniture equipped with capacitive proximity sensors is used to detect whole-body movements and postures. Subsequently, emotions of the user are inferred from these movements and postures. The publication by Rus et al. and the presentation of implicit foot gestures by Nierenberg et al. point to an application where information about the driver's emotional state could be obtained from foot gestures and position instead of explicit human vehicle interaction. Nonetheless, this would relate to Chapter 5 and research question RQ1 that are focused on vehicular human machine interfaces without explicit interaction.

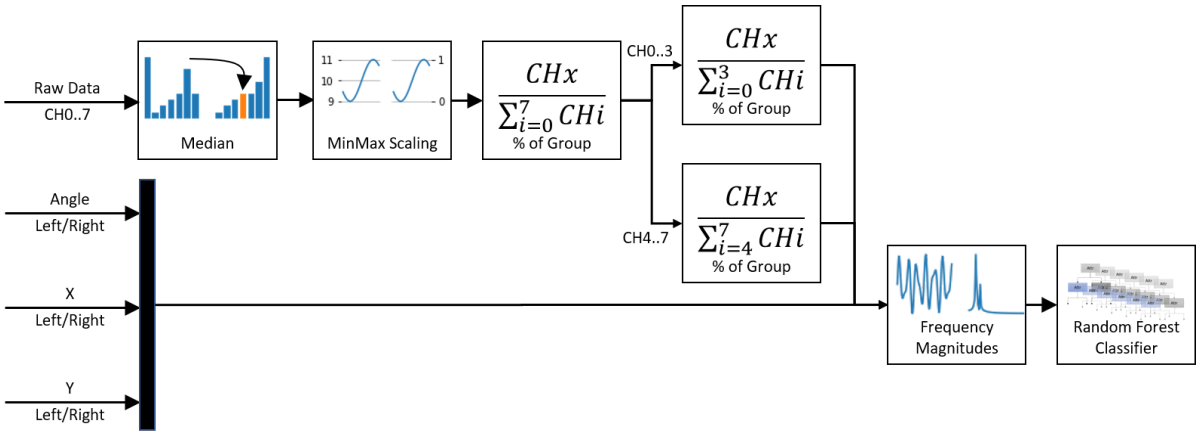



Figure 5.33.: Gesture recognition model

Now we discuss an algorithm for processing the data from the capacitive proximity sensors. The processing steps are shown in Figure 5.32. The first step is to apply a median filter with a window size of three to the raw channel data. Then the data is MinMax scaled to remove offset changes from measurement to measurement. The considered sensor value minimum is automatically adjusted in the running system. The maximum value is an empirically determined range of values added to the minimum value. The span is considered constant for all measurements. All values between the minimum and maximum values are linearly interpolated between zero and one. The ratio of each channel to the sum of all channels is then calculated. These data are then fed into position prediction models. In particular, the foot position in terms of rotation and translation, as required for the gestures, is predicted by six random forest regression models.

Previous processing results in an estimate of foot position and scaled sensor data. Using this data, gestures shall be recognized. The flow of the gesture recognition model is shown in Figure 5.33. Only the planar position as shown in Figure 5.31 is predicted by the regression models that are shown in Figure 5.32. Nevertheless, the Heel Tap and Toe Tap gestures involve a rotation around the x-axis. For a gesture recognition model, scaled sensor values are therefore included in the data. As depicted in Figure 5.33, the sensor channel data is similarly processed as for the position prediction models. With the difference that the capacitive proximity sensing data is then divided into a left and a right foot group. Each calculated value of the channels is divided by the sum of the respective group. Gestures are composed of a series of foot movements. In other words, a gesture is a temporally linked combination of foot positions. A feature vector consisting of multiple samples over time is chosen as the gesture representation. Each user has a unique interpretation of motion gestures. The time taken by a user to perform a gesture is unknown. For this reason, the number of samples in a time series is empirically determined after the first subjects have performed the gestures. The value is determined during the evaluation in Section 5.3.7. Using this empirically defined time window, the processed data of all channels and the position data of the feet are examined with a Fourier analysis. Then, only the amplitudes of the frequency spectrum are used to form the feature vector for a random forest classifier [Bre01]. In addition, the offset term of the frequency spectrum is removed so that only the relative position of the foot is considered and the focus is on the characteristics of the movement. Subsequently, the respective gesture performed by the user is predicted.

Now we have a concept for foot and gesture recognition. To enable the evaluation of the concepts, a prototype is built that implements the hardware and software design. In the prototype, a representation of the driver's

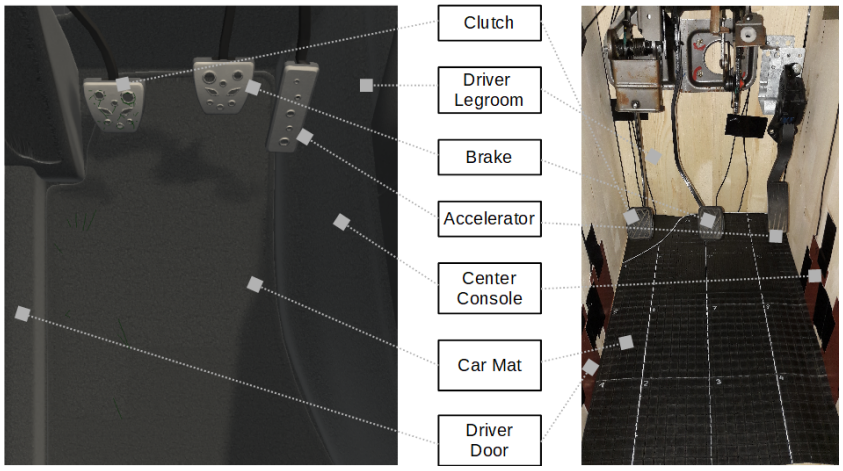



Figure 5.34.: Driver legroom mockup [FK19]

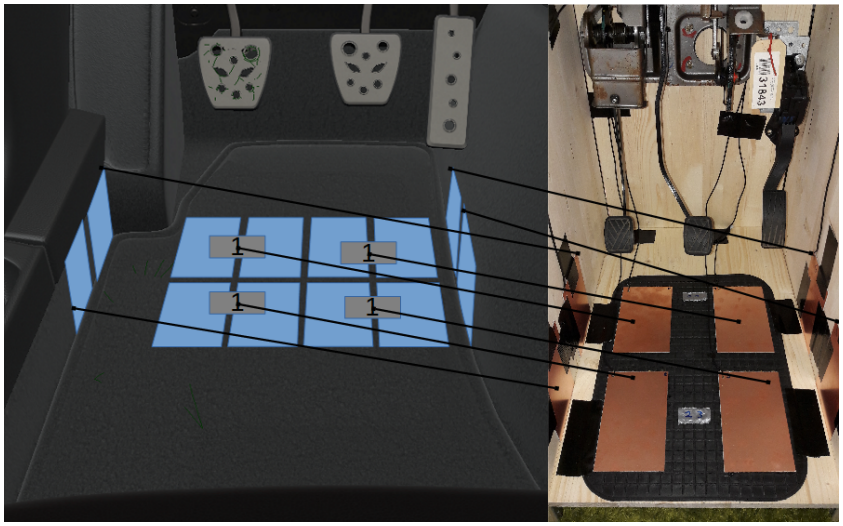



Figure 5.35.: Topology comparison between concept and mockup implementation [FK19]

footwell must be implemented. In addition, meaningful user data must be collected with the prototype to train and test the regression and classification models. A vehicle legroom mockup is therefore created. The driver's footwell is represented by a wooden box. The internal dimensions are 60 cm depth, 40 cm width and 60 cm height. The legroom mockup and an example vehicle legroom are shown in Figure 5.34. The mockup is shown on the right side. In particular, an ordinary rubber car mat is included in the mockup. An original set of car pedals is also included. The pedal set consists of clutch, brake and throttle pedals. In real cars, the movement of the driver's feet is restricted by the side door beam on the left and the center console on the right. This condition is represented in the mockup by the restriction of foot movement by wooden walls. The driver's movement towards the pedals is constrained by anthropometric constraints. Furthermore, the selected gestures require at least one fixed foot pivot point on the vehicle mat. Therefore, there is no significant spatial motion in the direction of the upper legroom, which is thus not constrained by the mockup. An off-the shelf [GPBB*13] capacitive proximity sensing toolkit with a sample rate of 25 Hz is selected. Eight channels for capacitive proximity sensing electrodes are included in the toolkit. For the electrodes of the mockup, a congruent shield is attached to the back of all sensing electrodes. All sensors are configured for operation in loading mode. A coaxial cable is also used to connect the sensing electrodes and the sensor. The cable core is connected to the sensing electrode and the copper mesh shield is connected to the shield. Furthermore, the sensing electrodes are integrated into the model according to the topology shown in Figure 5.30. Although twelve sensing electrodes are shown, only eight sensing electrodes are included in the mockup. Eight sensing electrodes are provided by the selected toolkit. Thus, the number of sensing electrodes under the foot mat is reduced from eight to four electrodes. The resolution for foot tracking could therefore be affected by the number of sensing electrodes. The updated sensing topology and implementation under the vehicle mat is shown in Figure 5.35. If the gesture recognition accuracy in the evaluation is below 90%, the number of electrodes would be increased to twelve. This would be enabled with a second OpenCapSense toolkit.

This mockup can now be used to collect data. However, a suitable approach must be defined to collect meaningful data for training and evaluating the models. Each model is based on supervised learning. So labeled data is needed. In gesture recognition, the labels depend on the gesture intent of the user. An application is developed where the intended gesture and start and stop can be communicated between the tester and the subject. During data collection, the instructor can capture relevant timestamps when gestures are started and stopped and which gesture is performed by the subject. An application window is displayed to the subjects. In this window, an image of the gesture to be performed can be displayed by the instructor. Subsequently, the subject should start the expected gesture. After the gesture is completed, the end of the gesture is communicated by the subject to the experimenter. The subject may report an unintended gesture execution. This cannot be recorded by the application during evaluation. Recorded time intervals between gesture start and gesture end are only an indication of the gesture position in the data. The measured data must be manually verified. The manual verification is done by analyzing the video data. This involves identifying the subject's intended gesture in the foot movements and labeling the start and stop. Thus, both gesture and non-gesture data can be generated using this approach. During the evaluation, a camera is integrated into the mockup to capture images of the leg space. While the measurement run is performed by the subjects, images of the leg space are captured. Each camera image of the leg space is accompanied by a data sample from the capacitive proximity sensing setup. A timestamp, label for the foot used, and intended gesture are included for each sample. The camera view and an example of a footwell image are shown in Figure 5.36.

After conducting the experiment, we have data in which the gestures are labeled. In addition, the foot position is required as input for the gesture classifier. Labels for the foot position must be included in the dataset. Since a camera is included in the mockup, the foot position can be derived from image processing. In a first attempt, the data was labeled without markers using optical flow-based algorithms, similar to the approach of Tran et al. [TDT12]. A spot check of the resulting labels confirmed that the use of optical flow analysis results in too

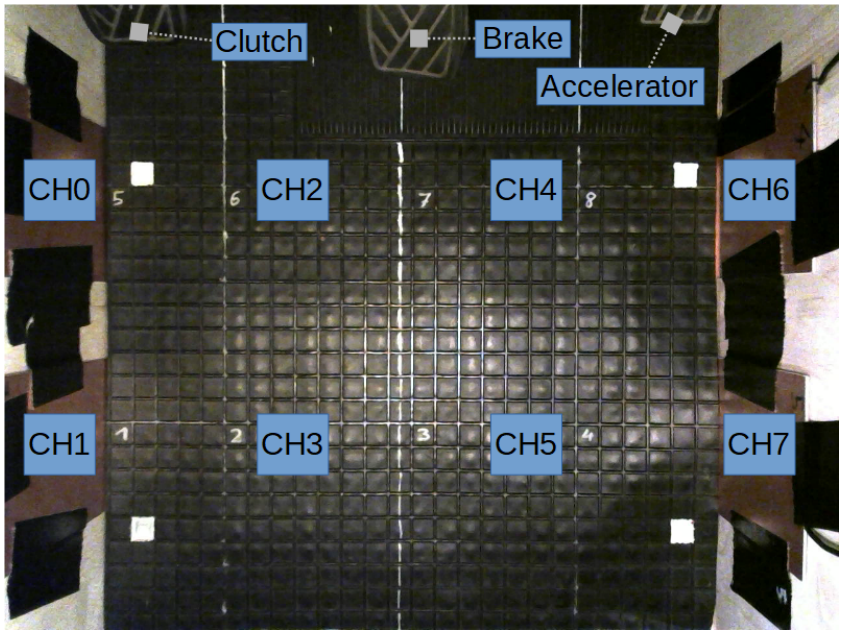



Figure 5.36.: Mockup view of used camera to capture driver feet [FK19]

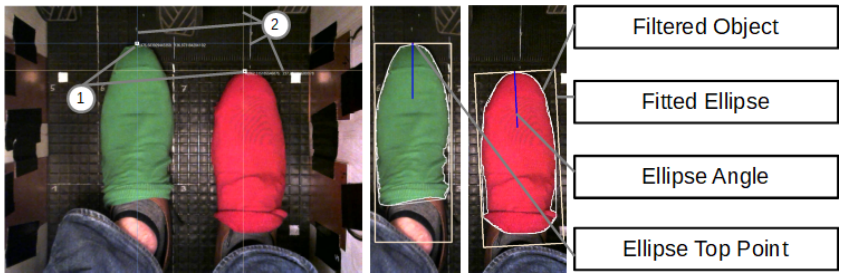



Figure 5.37.: Position labeling sample [FK19]

| Alias | Shoe Size EU | Shoe Size US-M | Age | Sex |
|---|---|---|---|---|
| User A | 39 | 6.5 | 55 | F |
| User B | 43 | 9.5 | 30 | M |
| User C | 38 | 6 | 33 | F |
| User D | 46 | 12 | 30 | M |
| User E | 38 | 6 | 29 | F |
| User F | 44 | 10.5 | 59 | M |

Table 5.6.: Evaluation subjects

many deviations from the true foot position. A color tracking-based approach is therefore used. Each user had to wear colored covers on their shoes. The input images are then filtered separately according to the colors used (green on the left, red on the right). This results in blobs. The blobs are then filtered to the appropriate size. After that, a rectangle with minimal area is fitted into the blob. An ellipse is also fitted into the blob. The intersection between the ellipse major axis and the fitted rectangle is the marker for the target plane position. The angle of the ellipse main axis is used as the foot angle in question. An example of a camera view with fitted elements and resulting labels is shown in Figure 5.37. With the data labeled, the processing models defined, and a mockup created for the user study, we can move on to evaluating the system.

### 5.3.7. Evaluate

The prototype and the application presented in Section 5.3.6 are used in the evaluation. As mentioned earlier, the application for evaluation is capable of displaying gestures to be performed by the subject and also displaying the current foot position of the subject. The evaluation is based on data from six subjects. The characteristics of the subjects are presented below, as well as the data collected during the use of the application.

A summary of the characteristics of the subjects in the study are shown in Table 5.6. The subject group is composed of three males and three females. Their European shoe size ranges from 38 to 46. The translation to US M shoe size is derived from a table and no direct participant measurement. Participants cover an age range from 29 to 59 years. The experiment follows a defined procedure. Before the subject can use the mockup, an introduction is given by the experimenter. In this introduction, the prototype is examined with the subjects without interaction. During the introduction, the foot space is not entered by the subject. In addition, each gesture is introduced to the subjects by the instructor and an example is shown of how the gesture could be performed. The measurement is then started without the subject's feet in the footwell. After that, the subject moves his or her feet into the booth and begins to move his or her feet in the cabin as required by the application. While the subject moves her or his feet, gestures to be performed are displayed in the application window. So, the subject starts to move her or his feet in the way he or she thinks the gesture should look like. In addition, subjects can inform the instructor if they have mixed up gestures or accidentally performed a different gesture.

Each of the four gestures is presented to each subject 20 times, ten gestures per foot (10 times left foot, 10 times right foot). A total of 480 gesture samples will be collected. In addition, 480 non-gesture samples will be collected. Specifically, 80 non-gesture samples per subject will be extracted across the collected data. The non-gesture samples will be extracted from the gesture sample data only. Based on this approach, a class distribution of 50% gesture samples and 50% non-gesture samples is collected. The gesture samples consist of four equally distributed gesture types. Thus, 12.5% of the entire dataset is associated with a particular gesture.

| Gesture | A | B | C | D | E | F | Sum |
|---|---|---|---|---|---|---|---|
| None | 80 | 80 | 80 | 80 | 80 | 80 | 480 |
| Heel Rotation | 21 | 20 | 20 | 20 | 20 | 20 | 121 |
| Heel Tap | 18 | 20 | 20 | 20 | 20 | 20 | 118 |
| Toe Rotation | 20 | 20 | 20 | 20 | 20 | 20 | 120 |
| Toe Tap | 22 | 20 | 20 | 20 | 20 | 20 | 122 |
| Sum | 161 | 160 | 160 | 160 | 160 | 160 | 961 |

Table 5.7.: Number of gesture samples

| Metric | X Left | Y Left | Angle Left | X Right | Y Right | Angle Right |
|---|---|---|---|---|---|---|
| $R^2$ | 0.95 | 0.99 | 0.83 | 0.95 | 0.98 | 0.83 |
| MAE | 6.12 | 4.20 | 1.21 | 6.73 | 5.05 | 1.19 |
| MSE | 231.00 | 141.64 | 17.78 | 302.33 | 244.24 | 15.65 |

Table 5.8.: Validation results: ten-fold cross validation

Due to this approach, the dataset is balanced in terms of gesture and non-gesture samples, and it is unbalanced with respect to specific gestures. This unbalanced design was chosen to reduce the false positive rate. There are many non-gestures included in the data because non-gestures are arbitrary movements. Gesture-like patterns could be included and lead to false positives. The actual number of samples per gesture and subject is shown in Table 5.7. While most gestures are executed by the users as desired, unintended gestures are reported by User A. For User A, Toe Tap is reported twice instead of Toe Rotation, Heel Rotation is reported once instead of Heel Tap, Toe Rotation is reported once instead of Heel Tap, Toe Rotation is reported once instead of Heel Rotation, and Heel Rotation is reported once instead of Toe Tap. In addition, User A performs a Toe Tap gesture before a Heel Tap gesture. All these unintentionally mixed gestures are added to the gesture dataset with the correct labels.

Even though the gestures are mostly executed as requested by the subjects, the actual execution of the gestures differs from subject to subject. To show this condition, an exemplary Heel Rotation gesture is selected from all users. The example is shown in Figure 5.38. The left foot angular displacement of each subject is shown on the left. Each image on the right of Figure 5.38 is taken from the evaluation. The minimum and maximum angular displacement of the displayed gesture is shown. While users B, D, E and F perform more than or equal to three repetitions, User A performs almost no full foot rotation repetition. In addition, peak-to-peak values differ from user to user. While User A shows a peak-to-peak value of approximately 53.5°, User F shows a peak-to-peak value of approximately 19.4°. Thus, the actual gesture execution is very individual for each subject.

In addition to gesture labeling, the entire evaluation process is used for foot position tracking. Since gesture recognition is based on foot tracking performance, foot position prediction is considered first in the evaluation. Both feet of the subjects are constantly monitored by a camera in the mockup. A total of 58,354 samples are collected over a period of approximately 58.5 minutes. Each of these samples is labeled as shown in Section 5.3.6. Each sample thus contains the information whether the left or right foot is visible, the plane position and the angle of the respective foot. The labels are estimated using image processing. Capacitive proximity sensing data is processed as shown in Figure 5.32. Thus, a feature vector is generated for each sample, which is composed

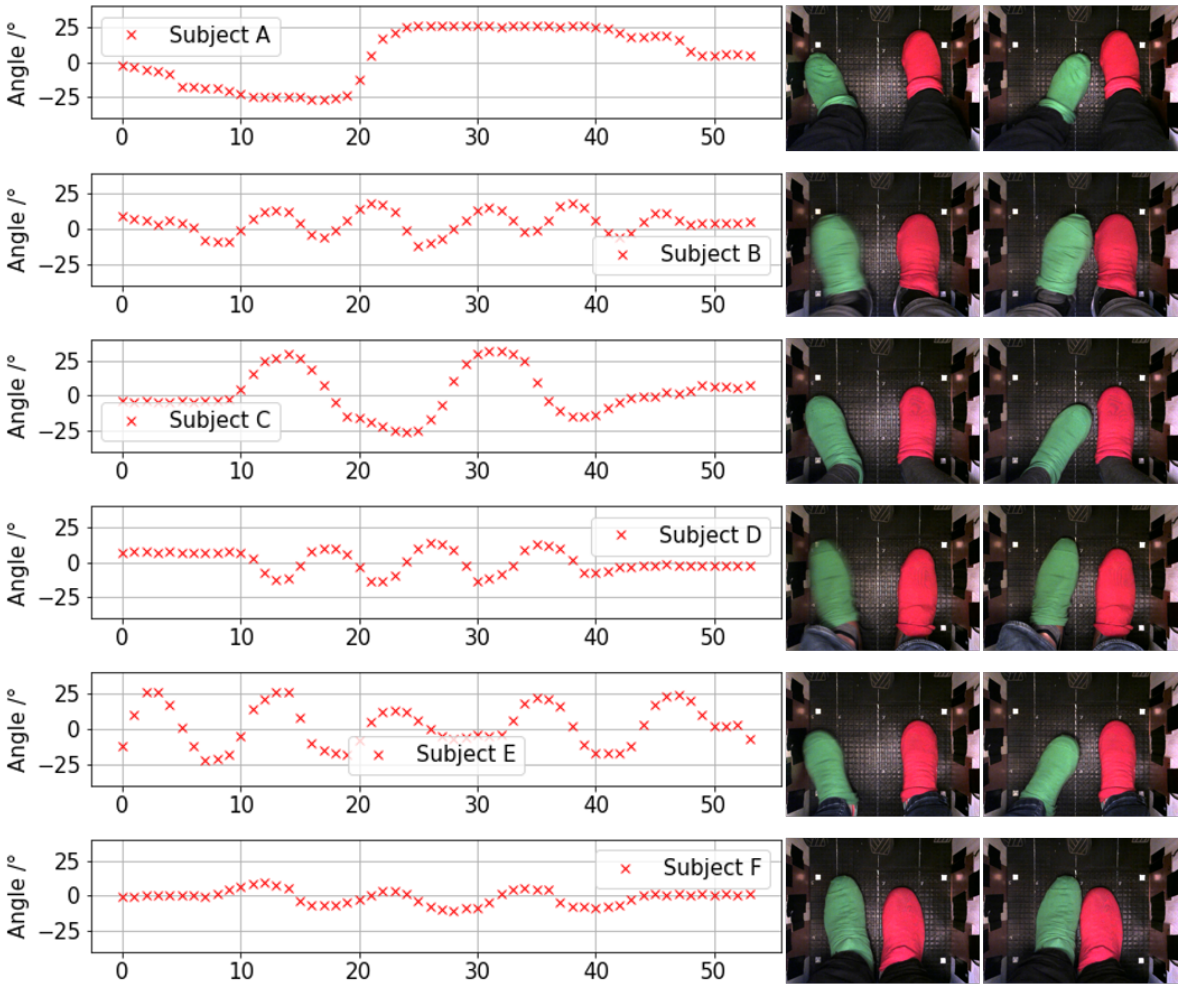



Figure 5.38.: Heel rotation sample angular subject characteristics

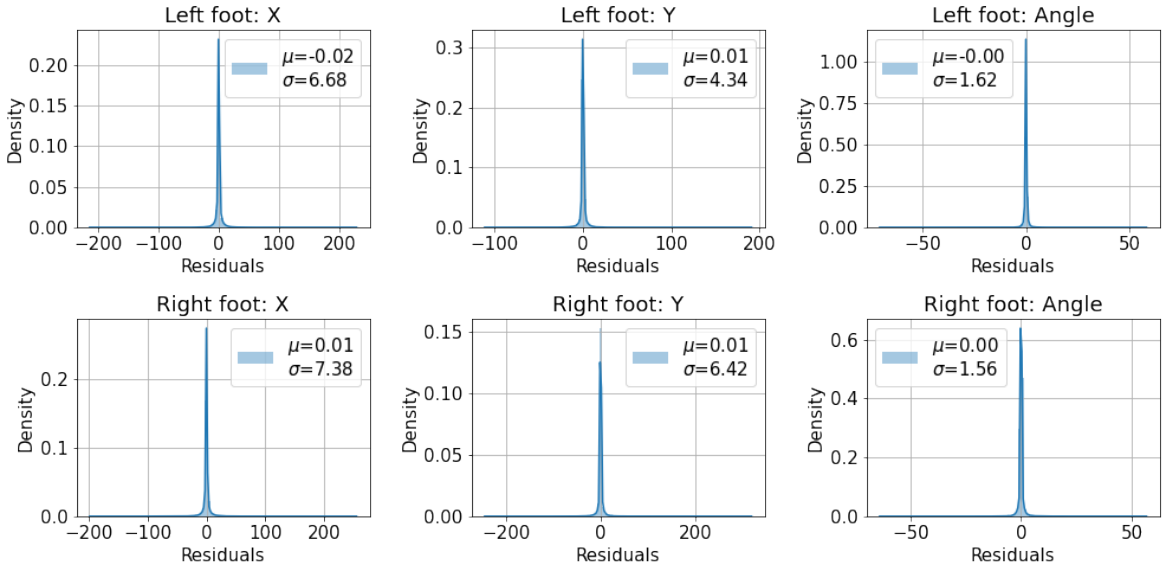



Figure 5.39.: Residual analysis for position tracking

of the processed capacitive proximity sensing data. Using this dataset of feature vectors with labels, the model is evaluated with a ten-fold cross validation. The results of this validation step are shown in Table 5.8. In summary, a coefficient of determination ($R^2$) greater than 0.95 is resulted for the translational axes x and y. A coefficient of determination greater than 0.83 is indicated for the rotation prediction. The mean absolute error (MAE) and the mean square error (MSE) are also listed in Table 5.8. For translational motion, a range of approximately 4.2 to approximately 6.7 pixels is measured for the mean absolute error (based on a mean value of approximately 23.26 pixels per centimeter, corresponding to approximately 0.18 cm to approximately 0.29 cm). In addition, a mean absolute error of about 1.2° is measured for the prediction of angular displacement. Thus, the translational position error, with respect to motions along the roll and pitch axes of the vehicle, is less than one centimeter. A model for each axis is then trained on the entire data set as a basis for gesture recognition. A histogram of the residuals of the models is shown in Figure 5.39. Since all residual distributions are centered around zero and a small σ is present, a valid model without bias is indicated. Now that promising models for foot tracking have been found, the data samples can be expanded to include the predicted foot position. This lays the foundation for the gesture recognition model shown in Figure 5.33.

Data of all subjects are combined into one dataset, which serves as the basis for training and evaluation of the random forest classifier. As stated in Section 5.3.6, the feature vector length has to be defined. The processing time for each gesture and user is analyzed. The analysis results in a value of 54 data points. Based on an average sampling rate of the acquired data of about 16.7 Hz, a gesture window of about 3.2 seconds is chosen. This window is chosen such that more than 90% of the executed gestures are within this window. Model validity is measured with a ten-fold cross-validation. The confusion matrix of this validation is shown in Figure 5.40. The data shown in the confusion matrix is the sum of all validation cycles. The number of correctly classified instances is 903, giving approximately 94% correct results. Therefore, no additional electrodes are added to the system. Instead, the current hardware setup is accepted as is.

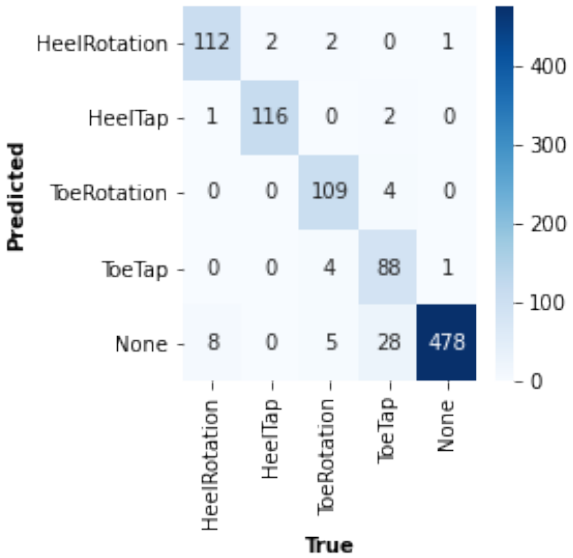



Figure 5.40.: Gesture recognition confusion matrix

Although the results on this proof of concept are promising, gesture classification could be improved by using more sophisticated classification models. For example, models like long short-term memory neural networks [HS97] could be applied. These models are designed to process sequential patterns because of their ability to maintain an internal state. Another approach might involve a two-level classification process. In the first level, the classes no gesture and gesture could be estimated by a classifier. If the class gesture is recognized by this classifier, the actual gesture type could be estimated by a second classifier. Thus, the number of classes for a classifier could be reduced and better performance could be achieved. Besides the performance of the models, the individual interpretation of gestures is an issue. As shown in Figure 5.38, different movements are exercised by all users to perform the same gesture. To increase the robustness of the gesture recognition model, many different gesture patterns must be selected by different users. Another question is whether the provided gesture set is compliant with natural user interfaces. Regarding this question, intuitive natural execution of the proposed foot gestures cannot be assumed. To use them to control, for example, a multimedia system, the user would have to memorize the provided gestures. However, only a small set of four gestures would need to be learned. The gestures could be recalled by the user after a short training period. Additionally, the prediction of foot position and movement could be used in future projects to assess the driver's emotions.

## 5.4. Discussion

The research question we are discussing is how can existing vehicle structures be used with capacitive proximity sensing to create new human computer interaction opportunities. There are several constraints in this question. The interaction system should be based on capacitive proximity sensing. An existing vehicle structure must be used as the basis for installing these sensors. Although not explicitly mentioned in the question text, natural

interaction must be considered for the application. The use of existing vehicle structures and capacitive proximity sensing already applies to research question one: How can we use existing vehicle structures to improve or replace in-vehicle human machine interfaces with capacitive proximity sensing. Research question RQ1 is explicitly addressed in Chapter 4. Nonetheless, interaction is the major distinction from the first research question and Chapter 5. To address this distinction, an approach for developing vehicle-human interaction that can be used to gather evidence for RQ2 is presented in Section 3.1.11. Basic steps for solving real-world problems and developing an interaction system for vehicles based on capacitive proximity sensing are presented. While these steps are also applied to in-vehicle human machine interfaces, the concept is enriched with considerations for natural interaction. *Social awareness and skills*, *body awareness and skills*, *Naïve physics* and *environment awareness and skills* have to be considered. Hence, all elements of the research question are covered by the concept. Nonetheless, the theoretical approach has to be tested. Three applications are developed based on the concept. The addressed elements of RQ2 are presented in the following paragraph. Subsequently, each application will be discussed briefly with related issues and opportunities. Afterwards, the theoretical concept is discussed. In particular, what are the issues and opportunities that occurred due to the realization of the concept.

Although the development of the applications required additional sensors to enable the capabilities of the final system, the final systems are based only on capacitive proximity sensing. Capacitive proximity sensing has been used to develop applications for pointing devices and gesture recognition. Specifically, two hand-based interaction systems and one foot-based interaction system were developed. In addition to the technical implementation of the sensor system and tracking the human body for interaction, potential applications for interaction were presented in each section of Chapter 5. Therefore, not only the technical feasibility is presented, but also meaningful applications are developed so that existing problems in vehicles can be addressed. Each application is based on an existing vehicle structure. In particular, the authentication and pointing application for Head-Up-Displays are based on the steering wheel. The foot gesture recognition application is based on the footwell of the vehicle. Nevertheless, only two vehicle structures were used in Chapter 5, but further elements like the interior roof are named. There are other structures that could be used for interaction, such as the inside of the door or the sunshade. The concept may not be applicable in all cases. Nevertheless, the present concept has proven to be effective for all developed applications. The practical application of the concept is very similar, whether the application is related to the footwell or the steering wheel. In addition to the vehicle structure, the concept demands that natural interaction is taken into account. Elements like *body awareness and skills*, *social awareness and skills*, *Naïve physics* and *environment awareness and skills* are considered for each application. Gesture interaction, which does not require the driver to learn any new commands other than her or his own, is included in the application for authentication. Deictic gestures, which take into account a segmented driving situation so that the driver can point to entities in her or his environment, are considered in the application for the head-up display. The fact that emotional states of the driver can be derived from the foot position is further considered in the foot gesture recognition. To accommodate natural interaction, the final set of foot gestures is thereby reduced to four gestures so that the cognitive load on the user can be kept low. In general, all applications show reasonable performance. This demonstrates how an existing vehicle structure with capacitive proximity sensing can be used for in-vehicle human machine interaction. Nevertheless, advantages and disadvantages are highlighted for each application. These will be discussed in the next paragraph.

The first application considered is developed to improve authentication in vehicles. Among other vehicle structures and sensor systems, a steering wheel equipped with capacitive proximity sensing is considered most suitable to meet the conditions of non-contact interaction, privacy protection, and no visible impact on the interior. Patterns for authentication can be freely drawn. Short signatures are possible as well as combinations of multiple symbols. An evaluation was conducted to test the usability of the system and validate the authentication mechanism. Although the results are positive for hand tracking and the authentication mechanism, the authentication mechanism could be improved. In particular, the hand speed is neglected. Security of the authentication

could be improved if the hand speed is included in the pattern similarly to a signature. The authentication model is based on a simple distance metric. A more sophisticated model could improve the authentication. Based on the same vehicle structure, a pointing device for head-up displays is developed in Section 5.2. A modified sensor topology improves hand position estimation compared to the authentication system. In a user study, the system is evaluated in terms of usability. Although the system is new to the users, the usability is rated almost equivalent to a touchpad. Each user was able to point at specific elements of the head-up display. In addition to the technical implementation, interaction concepts are also examined. In particular, two approaches are analyzed. In one approach, the user could simply point to elements of her or his environment and a context-sensitive application is triggered to display additional information. In a second approach, the driver is shown possible interaction points in the environment so that the user knows where information can be displayed. The second approach is considered more compliant with natural user interaction, as the user is not surprised by abruptly displayed information. Although good results are shown in the evaluation, the application can be improved with more training data. The current application is based on a two-dimensional input. Nevertheless, the three-dimensional input of the hand can be captured. Thus, the opportunity for three-dimensional interaction is not used. Future studies should take the chance to use three-dimensional interaction concepts. Usability must be tested under real-world conditions. For this reason, a working environment segmentation needs to be combined with the hand tracking concept under real conditions so that the actual cognitive load can be measured. In the next application, the focus is shifted from hands to feet. There is little research on foot gestures. As such, there are new possibilities for interaction in automotive environments based on capacitive proximity sensing. Similar to the other systems, the sensors are invisibly integrated into an existing vehicle structure. Unlike the other applications, the vehicle structure used is the vehicle leg compartment. The application is shown in Section 5.3. The application has been developed from scratch and concepts for interaction have been designed. The concepts were integrated into a vehicle legroom mockup to form a prototype for evaluation. The evaluation is based on a user study with six subjects. In the user study, a recognition rate of 93% correctly classified gestures is achieved. Although individual gesture execution varies widely among users, robust recognition is ensured. The gesture set for the application is developed with natural interaction considerations. Nevertheless, the set still needs to be learned by the user. Other applications for driver mood recognition are mentioned as possible applications. For future work, the foot gesture recognition model can be improved with more topics so that diverse gesture executions are covered. Also, the system needs to be included in real driving conditions, e.g., automated driving, to test possible applications and investigate usability while driving.

After we talked about the specific applications of Chapter 5, in particular the advantages and open questions for the specific approach, we move now to the analysis of the application of the concept and how research question RQ2 is addressed. Research question RQ2 is formulated as: *How can we use existing vehicle structures to provide new ways of human computer interaction using capacitive proximity sensing?* It should be noted that the focus of this research question is on capacitive proximity sensing, similar to research question RQ1. It is shown in Chapter 5 how applications can be built based on capacitive proximity sensors for vehicular human machine interaction. Only existing vehicle structures are used. The provided concept in Section 3.1 helped to identify issues that should be tackled. Because of the application of the concept, the developer of the systems must think about meaningful applications so that the developed applications provide meaningful interaction. Nonetheless, the term *new ways of human computer interaction* is used in research question RQ2. In terms of basic human emissions tracking, gestural interaction with hands or feet in vehicles is not entirely new. Nonetheless, the way these gestural interaction capabilities are used is a new type of interaction. In particular, the envisioned authentication mechanism and deictic gestures to control the head-up display have not been found in the literature or in manufactured systems. Similarly, the proposed type of foot gesture recognition appears to be novel. In addition, other possible applications for limb tracking are mentioned. In particular, driver mood recognition based on foot gestures could provide new information for driver monitoring systems. This also shows that the

extended concept for interaction that is presented in Section 3.1.11 is able to generate natural interaction or at least advises the developer to think about natural interaction. As already stated in Section 4.3, the benchmarking process that is used to identify the best sensor system is considered to be suited for research applications. In particular, some metrics such as unobtrusiveness are still based on assumptions made by the developer and may be biased as a result. It is difficult to estimate metrics for, for example, processing or calibration complexity when the system has not yet been designed. In summary, the applications developed using the concept provide clues to research question RQ2. However, the research question is formulated in a very general way. Therefore, more systems based on capacitive proximity sensing in vehicles for human machine interaction are needed to gather further evidence.

# 6. Assessment of privacy concerns caused by mechanisms in-vehicle human machine interfaces

While Chapter 4 and Chapter 5 mainly address the technical problems of research questions RQ1 and RQ2, we now deal with the evaluation of a special property of sensor systems for human machine interfaces in vehicles: data privacy compliant behavior. Since not all sensors are comparable to capacitive proximity sensing, the focus is on camera-based systems. The judgment of whether these systems are privacy compliant is a matter of regulations, but the regulations do not necessarily match the user's perception. Due to this discrepancy, research question RQ3 is divided into two parts: the law's perspective and the user's perspective.

Before we begin the evaluation, the motivation for studying privacy concerns is captured. One motivation is that personal information has become very valuable for enterprises. Enterprises which include data collection services rank among the most valuable businesses. For example, Touryalay et al. [TSM18] list Amazon.com in second place, Alphabet in third place, and Facebook in fifth place in terms of market value. As shown by Alexa Internet [Ale19], websites of these companies, such as "google.com" or "Youtube.com", are at the top of the most visited. Thus, they play a significant role in the daily life of people. As shown in Section 3.2.1, vehicles become massive data hubs. They are of interest for enterprises which collect data or evaluate customers on the basis of data, such as insurance companies [RMdV19]. Although data collected in vehicles may be of interest to companies, the collection of privacy-sensitive data such as facial images can lead to privacy issues. Countermeasures are installed by the European Union (EU) through the adoption of the "General Data Protection Regulation" (GDPR) [Cou16]. This law regulates, for example, the transfer of personal data from the EU to foreign countries. The law also includes paradigms such as "privacy by design" and "privacy by default", which play a major role in the regulation (GDPR Article 25: *"Data protection by design and by default"*). Privacy by design means that product development should prevent data protection-relevant functionalities from being created. Privacy by default means that the initial settings of the data collection should foresee the most privacy-friendly behavior.

Data collection possibilities are already ubiquitous in people's everyday lives. Thanks to smartphones, for example, 28% of US citizens were almost constantly online in 2019 [PK19]. Applications for mobile phones (apps) make it easier for companies to collect data. Users exchange sensitive information that is supplemented by additional sensors. This enables companies to derive detailed user profiles [Yal17]. Similarly, vehicles offer a plethora of sensor systems. These sensors are actually used to enhance safety, comfort, and route optimization. In addition, primarily web service-based companies such as Alphabet are entering the automotive sector. Mobile phone to vehicle interfaces, like Android Auto [Goo] or Apple CarPlay [App20], are already available [Ulr15]. Companies have already developed business models for the data collected from vehicle users. There are positive examples such as safety functions or comfort features. For example, navigation can be optimized by using traffic information. Heart rate monitoring can inform drivers about their fitness to drive, but there are also examples that lead to data collection that is not in the driver's best interest [SG18]. For example, insurance companies could buy information about collected driving behavior. This may make drivers uninsurable. In addition, some

driver monitoring systems include cameras pointed at the driver. Health insurance companies could collect more sensitive information about people's health constitution. Health constitution could be inferred from identified smokers, frequent meals while driving, or corpulence.

Customers may decide wisely which systems to install in their cars. Nevertheless, research has shown that there is even a difference between security-conscious and privacy-conscious customers [CB17]. For systems such as driver fatigue detection, the consequences of data collection and the safety aspects of vehicle systems may not be obvious. Due to the privacy-security knowledge gap [CB17], potential vehicle customers may furthermore behave different at system selection. This may influence vehicle manufacturers' system development decisions. If the product target group is focused on privacy- and security-preserving technology, manufacturers should pay attention to privacy by design. A target audience that prefers functionality over privacy may choose the lowest-cost system with the highest functionality. Moreover, due to the complexity of systems, individuals often make decisions based on incomplete knowledge [AG05]. Emerging security issues in connected vehicles make the decision even more complex. As indicated by Volkswagen [SZH18], software complexity is growing. By its very nature, this makes future exploits possible. Currently secure software may become vulnerable in the future. Research already recognized the need for frequent updates in the future [HKS*19, KDC18]. Business models in the automotive industry that require data collection may rely on sensor systems that raise privacy concerns. It is unclear whether vehicle customers have privacy concerns when selecting a technology package. Therefore, vehicle users' perceptions of privacy must also be evaluated.

We will therefore interview vehicle users about their privacy concerns, regarding selected sensor systems for human machine interfaces. In addition to other sensor systems, we place particular focus on cameras. Although privacy concerns may arise from the use of cameras, there are applications where cameras are imperative because they are able to measure certain symptoms. For example, one application of cameras is fatigue detection systems. Specifically, cameras are used to track eye position and eyelids. If this symptom of fatigue is mandatory, there may not yet be a suitable other detection system. Nevertheless, cameras are also used for gesture recognition. Gesture recognition shows a variety of working systems that do not rely on cameras and have already been developed for vehicle systems. The main system of this thesis are capacitive proximity sensors, and they are considered as an alternative to, for example, camera-based systems. Cameras were also recognized as a possible alternative in all applications of Chapter 4 and Chapter 5. Besides these applications, capacitive proximity sensing is used in various gesture recognition systems. It is one of the systems that can be compliant with the law and provide sufficient capabilities [FK17a, BFMW15, BNS*14]. The compliance of capacitive proximity sensors is also part of the investigation in this project. Even though capacitive proximity sensors are available and may be compliant with privacy by design, the vehicle user may not even know of their existence. The widespread use of cameras may imply that the vehicle user has no choice [BTRB17]. Even though a sensor system may not be privacy compliant, vehicle users may not have privacy concerns about the system. The voice of the vehicle user is therefore recorded.

In summary, there is a legal perspective applied to the human machine interface in vehicles and a user perspective. The perspective of the law is discussed in Section 6.1. Section 6.1 is based on *Privacy by Design: Analysis of Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces* [FK20b]. The user's perspective is covered in Section 6.2. Section 6.2 is based on *Privacy by Design: Survey on Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces* [FK20c]. Section 6.1 and Section 6.2 aim to apply the approaches presented in Chapter 3 to real applications or under real conditions. Hence, in Section 6.1 existing vehicular human machine interfaces are analyzed with regard to regulations. Further, in Section 6.2 a survey is conducted which contributes to the question if capacitive proximity sensing can contribute to the acceptance of vehicular human machine interfaces. Focus is set on the comparison of cameras and capacitive proximity sensing.

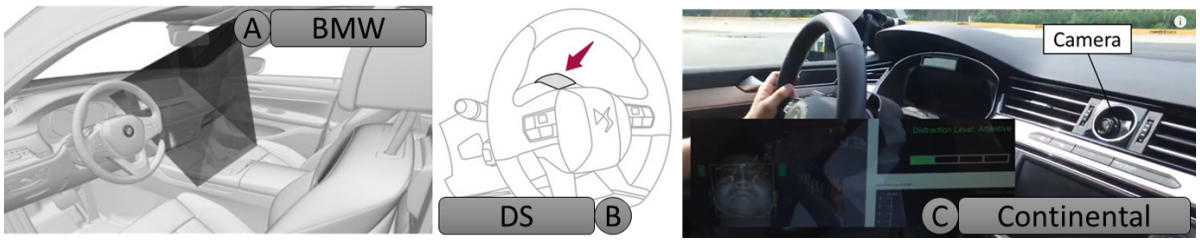



Figure 6.1.: Table 6.1 sample systems [Bay18, DS 19, Ang]

## 6.1. Analysis of existing systems from the law's perspective

The formulation of research question RQ3 is extended to: *Can capacitive proximity sensing contribute to the acceptance of vehicular human machine interfaces with regard to privacy concerns concerning regulations by law?* to emphasize focus on the perspective of law. As shown in Section 3.2.1, the analysis follows a subset of possible privacy threats and the introduced "Purpose - Opportunity - Difference". Examples of human machine interfaces in vehicles that are not based on capacitive proximity sensing are selected in Section 6.1.1. Section 6.1.1 includes the original use of the device and the data collected by specific sensor systems. A similar set for vehicle-based human machine interfaces based on capacitive proximity sensing is then established in Section 6.1.2. The sensing systems have a specific purpose and may interfere with the purposes of other systems based on the same sensors. So, there might be a difference between the purpose of the systems and the opportunities of the sensor system. This is presented in Section 6.1.3. Based on the analysis of the system, hypotheses emerged with particular focus on camera and capacitive proximity sensing. These hypotheses are formulated in Section 6.1.4.

### 6.1.1. Selected driver vehicle interfaces

We now select several vehicular human machine interfaces which are designed on specific purpose. These system's sensor system and their purpose require, as presented in Sections 2.4.1 and 2.4.2, less information than captured. The selected vehicular human machine interfaces are not based on capacitive proximity sensing. Each selected system is presented in Table 6.1. This table shows the system focus of each system and the sensors required. The system focus points to user entities to infer motion so that conditions or inputs can be captured for control. Notably, many systems have a similar purpose to attention detection. The attention systems presented (# 1, 3, 5, 6), which are dedicated to detecting attention or fatigue, are based on cameras (which may be infrared cameras). Attentiveness is assessed by analyzing images of the driver's head. These images are used to derive head position and eye opening. Head position and eye opening can provide information about driver fatigue, such as when the driver stares or when his or her eyes are nearly closed [DG98]. Besides attention assistants, gesture control is another domain of the human machine interface in vehicles. Systems # 2, 4 and 10 of Table 6.1 are dedicated to capture gestures. These systems rely on cameras. They are used to capture hand movements (Figure 6.1, *A*), the upper body or the whole driver body. In addition, a microphone is required in the # 10 system. It is used to capture the driver's voice commands. Based on the captured images, gestures such as pointing (one finger), wiping and circular hand movement are derived and enable control. Examples of regions of interest for camera-based systems and the location of cameras are shown in Figure 6.1.

| # | **Enterprise**<br>Application | System focus | Sensors |
|---|---|---|---|
| 1 | **BMW** [Bay18]<br>Attentiveness assistant | Head position<br>eye opening | Camera |
| 2 | **BMW** [Bay18]<br>Gesture control | Hand movement | Camera |
| 3 | **DS** [DS 19]<br>Driver attention<br>warning | Head position<br>eye opening | Infrared camera |
| 4 | **PSA** [Gro16, JMM*15, EL16]<br>Gesture control | Hand movement<br>Upper body | (Time of flight) camera<br>infrared sensors |
| 5 | **Continental** [MB14]<br>Adaptive emergency brake<br>and steer assist<br>systems based on<br>driver focus | Head position | Camera (monocular,<br>binocular, array) |
| 6 | **Continental** [SBM*16]<br>Adaptive driver assist | Driver face | Camera |
| 7 | **Visteon** [SMG*04]<br>Vehicle personalization<br>via biometric identification | Fingertips | Fingerprint sensor |
| 8 | **General Motors** [CL14]<br>Hierarchical recognition of<br>vehicle driver and<br>select activation of<br>vehicle settings based<br>on the recognition | Driver face, voice | Microphone, camera |
| 9 | **Volvo** [LHB13]<br>Method for performing<br>driver identity<br>verification | Voice, face<br>fingertips | Camera, microphone |
| 10 | **Honda** [DCH*14]<br>System and method<br>for controlling a<br>vehicle user interface<br>based on gesture angle | Whole body | Camera, microphone |
| 11 | **Hyundai** [HKOM16]<br>Driver recognition system<br>and recognition method<br>for vehicle | Driver feet | Camera |

Table 6.1.: Vehicular human machine interfaces without capacitive proximity sensing

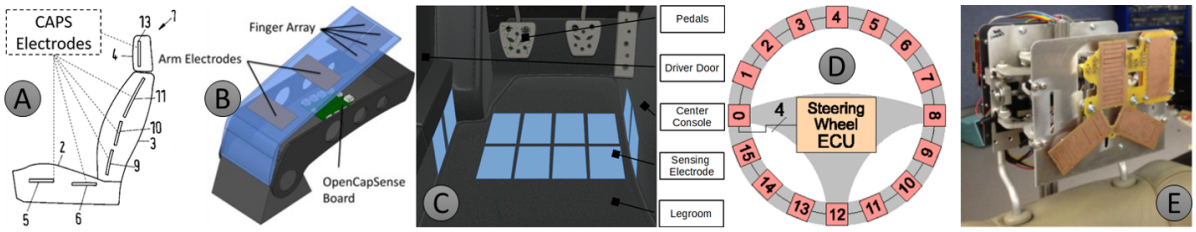



Figure 6.2.: Table 6.2 sample systems [BWF16, BNS*14, FK19, BLRS09, ZLR15]

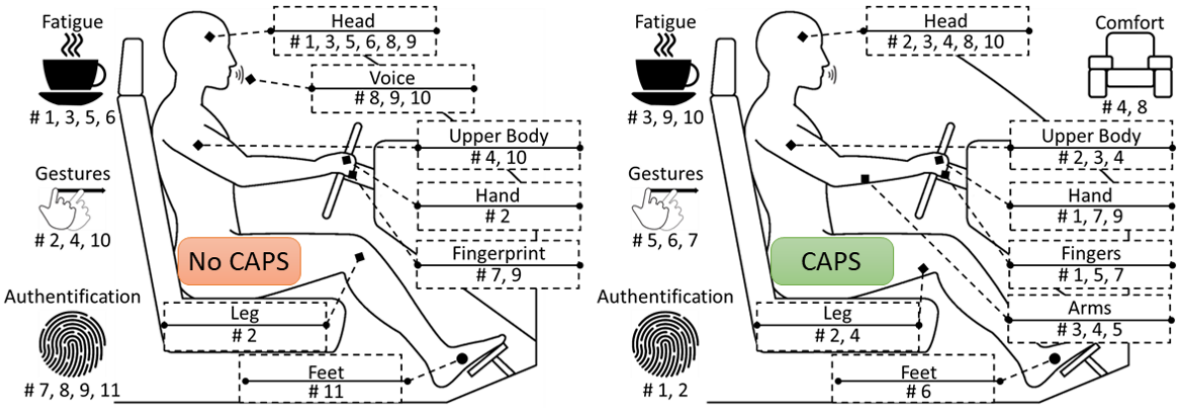



Figure 6.3.: System overview: left - Table 6.1; right - Table 6.2 [FK20b]

There is another relevant purpose of human machine interfaces in vehicles: driver recognition and identification. Systems capable of identifying or recognizing the driver are # 7, 8, 9 and 11 in Table 6.1. The # 7 system includes a fingerprint sensor. It should be difficult to capture more information than the fingerprint (which is of course biometric data) with a fingerprint sensor. Nonetheless, the other systems rely on at least a camera. In addition, # 8 and 9 require a microphone to identify the driver. The region of interest of the cameras varies. While # 8 and 9 capture images of the driver's face, # 11 captures images of the driver's feet. All of these methods are used to measure driver identity. These are all areas covered for systems that do not rely on capacitive proximity sensing. To further illustrate the system setup and for later comparison with systems based on capacitive proximity sensing, an overview of these systems from Table 6.1, their areas and the regions recorded is shown in Figure 6.3, left. Most of the required information is captured by cameras, and three systems also record the driver's voice.

### 6.1.2. Selected driver vehicle interfaces based on capacitive proximity sensing

We now consider alternative systems based on capacitive proximity sensors. An overview over the considered alternatives to systems in Table 6.1 are presented in Table 6.2. Similar domains to those shown in Table 6.1 are covered by each system. Hence, those systems can be compared with each other. The domains are authentication, gesture recognition, attentiveness and in addition comfort. The first domain we discuss is authentication and

| # | Publication | Application | System focus |
|---|---|---|---|
| 1 | AuthentiCap - A Touchless Vehicle Authentication and Personalization System [FK17a] | Authentication | Hands<br>Fingers |
| 2 | A method for determining a person's identity on a seat of a vehicle [BWF16] | Identification | Head<br>Upper body<br>Legs |
| 3 | CapSeat: Capacitive Proximity Sensing for Automotive Activity Recognition [BFMW15] | Fatigue | Head<br>Back<br>Arms |
| 4 | CapSeat: Capacitive Proximity Sensing for Automotive Activity Recognition [BFMW15] | Comfort | Head, Back<br>Arms<br>Legs |
| 5 | Towards Interactive Car Interiors: The Active Armrest [BNS*14] | Gestures | Arm<br>Fingers |
| 6 | Enabling Driver Feet Gestures Using Capacitive Proximity Sensing [FK18, FK19] | Gestures | Feet |
| 7 | HUDConCap - Automotive Head-Up Display Controlled with Capacitive Proximity Sensing [FK17b] | Gestures | Hands<br>Fingers |
| 8 | Vehicle Occupant Head Position Position Quantification Using an Array of Capacitive Proximity Sensors [ZLR15] | Comfort | Head |
| 9 | Distributed sensor for steering wheel grip force measurement in driver fatigue detection [BLRS09] | Fatigue | Hands |
| 10 | Developing a multi sensors system to detect sleepiness to drivers to drivers from transport systems [DCN*16] | Fatigue | Head |

Table 6.2.: Vehicular human machine interfaces based on capacitive proximity sensing

identification. Two authentication/identification systems (# 1 and 2) are shown in Table 6.2. Although they are in the same domain, both are based on different methods for identifying or authenticating users. System # 1 uses password-like gestures that are defined by authenticated users themselves. The password is based on certain hand movements. Since the steering wheel is within reach of the user's hands, the monitoring area for the detection system is around the steering wheel. Monitoring is facilitated by an array of capacitive proximity electrodes. These electrodes are integrated into the steering wheel. If the user's hand moves within the detection range of the sensors, a password gesture is detected. Hands-free hand positions are thus detected by the system. In contrast to system # 1, capacitive proximity sensors are integrated into the driver's seat in system # 2. The sensing topology of system # 2 is shown in Figure 6.2 labeled with *A*. Identification processing is activated when the user takes a certain posture on the seat. The driver is then identified based on her or his capacitive proximity sensing profile. The system focuses on the area between the driver's seat and the driver's head, upper body, and legs. A similar electrode setup as in system # 1 is used in system # 3.

The investigation of the system # 3 leads to the next considered domain of human machine interfaces in vehicles based on capacitive proximity sensing. This domain is the detection of attention or fatigue. Fatigue detection is enabled in system # 3 by various symptoms such as nodding, yawning, and gaze detection. Suspicious steering wheel movements are also detected. Electrodes are incorporated into the driver's seat to detect the associated entities of the human body. For example, sensors are incorporated into the headrest to detect head position. Sensors are built into the back of the driver's seat to detect yawning, and sensors are built into the side bolsters of the seat to derive arm movements associated with steering wheel movement. The focus of the system is thus on the area between the seat and the driver's head, upper body and upper arms. Another system in this area is system # 10. Based on the information about the head position, system # 10 derives the driver's fatigue. The headrest is used as a capacitive proximity sensing mount for fatigue detection. The system focus is thus on the area between the seat and the head. Other fatigue systems rely on the steering wheel as a base for capacitive proximity sensing electrodes. Similar to system # 1 of the authentication domain, system # 9 integrates capacitive proximity sensors into the steering wheel. Signs of fatigue are derived from variations in the driver's grip force. The focus of the system is thus on the contact between hands and steering wheel. The sensing topology of system # 9 is shown in Figure 6.2 labeled with *D*.

Gesture recognition is the next considered domain of vehicular human machine interfaces. Gesture recognition is provided by capacitive proximity sensing systems # 5, 6 and 7 of Table 6.2. These systems focus on hand, finger, or foot movements. The movement of these extremities results in certain gestures. Hand and finger gestures are provided via a driver armrest equipped with capacitive proximity sensing in system # 5. The electrode topology of system # 5 is shown in Figure 6.2 labeled with *B*. Driver arm and fingers are therefore in focus of the system. Contrary to system # 5, hand movement is tracked using a capacitive proximity sensing equipped steering wheel in system # 7. The setup is similar to the one of system # 1. The system focus is on driver hands in the area of the steering wheel, like in system # 1. A gesture recognition system which is not based on hand gestures is represented by system # 6. This system enables driver foot gestures. The sensing electrode topology is shown in Figure 6.2 labeled with *C*. In this system, capacitive proximity sensors are integrated into the vehicle legroom. Due to this setup, feet movement can be tracked. The system focus is on the driver's feet. Aside of identification, fatigue detection and gesture recognition, comfort features are provided by systems # 4 and # 8. System # 8 is shown in Figure 6.2 labeled with *E*. Due to the electrode topology attached to the headrest, system # 8 is able to automatically adjust the driver's headrest based on the output of the headrest sensors. The focus of the system is thus on the area between the seat and the head. A similar topology to that of system # 4 is also implemented in ordinary office furniture [BFW15, BSF15].

### 6.1.3. Purpose - Opportunity - Difference

In Section 6.1.1 and Section 6.1.2 two sets of vehicular human machine interfaces are presented. Based on these sets, we now conduct an analysis based on "Purpose - Opportunity - Difference". The metric "Purpose - Opportunity - Difference" aims to reveal conflicts with privacy by design, based on the definition of privacy that was presented in Section 3.2.1. The analysis begins with systems that do not rely on capacitive proximity sensing. These systems are shown in Table 6.1. Gesture recognition is the first considered domain. The purpose of systems # 2, 4, 10 of Table 6.1 is gesture recognition. Recording more information than just gestures could violate the privacy-by-design paradigm. In particular, the opportunities provided by the captured data could violate privacy-by-design. To capture gestures, the sensors of those systems partly capture images of the whole driver body (# 10). The captured images provide further opportunities because vehicle manufacturers already use those images to identify the driver (Table 6.1: # 8, 9). This is an invasion of privacy as biometric data is collected. Captured data is further used to derive driver attention (Table 6.1: # 1, 3, 5, 6). Since this may be an individual's performance indicator, there may be an interference with privacy through "profiling". The evaluation of driver images may offer further opportunities. Already patented systems like [DHKP17, WEDGF*18, AKH19] derive information as texting, smoking or eating. All of those are based on driver image processing. Patent [WEDGF*18] already points to remote state evaluation by third parties. The ability to profile and identify subjects based on sensor output is therefore provided by camera-based systems, even if the original purpose of systems # 2, 4, 10 is only gesture recognition.

While these systems do not rely on capacitive proximity sensing, systems that do rely on capacitive proximity sensing can also provide opportunities unrelated to purpose. The "Purpose - Opportunity - Difference" metric is therefore applied to these systems. Systems based on capacitive proximity sensing provide gesture recognition. At first glance, capacitive proximity sensors cannot directly capture information such as identity or facial images, and they do not appear to conflict with privacy. Nonetheless, capacitive proximity sensing-based systems like # 1, 2 of Table 6.2 are used to authenticate and identify users. Both systems' sensor design is similar to those that provide gesture recognition or comfort enhancement (Table 6.2: # 7, 8). Gesture recognition systems with capacitive proximity sensing may therefore have possibilities that interfere with the definition of privacy. Nevertheless, there is no authentication or identification based on the captured data itself. Both systems rely on prior user interaction. Identity cannot be directly inferred from the data output by # 7 and 8. If we compare the captured images or voice of a subject with the data from capacitive proximity sensing, then the images or voice provide a set of target information for identification. This means that the identifiers are already included in the sensor data. When a camera captures the upper body to capture hand gestures, the position of the hand is already labeled in the captured image. Similarly, the driver's face, which is visible in the captured data, is also visible and therefore labeled. In contrast, if capacitive proximity sensors are used, the data provided is a list of unknown target correlations. Capacitive proximity sensing-based systems require additional information such as sensor topology and subject information for identity mapping. This means that deriving further privacy-relevant information from capacitive proximity sensing data is more difficult than for images or voice data, because the labels for privacy-relevant information are not present in the data.

### 6.1.4. Hypotheses about privacy concerns of driver monitoring systems

In Section 6.1.3, several systems based on capacitive proximity sensing or without capacitive proximity sensing were analyzed. The analysis is based on the difference between their purpose and their opportunities, where opportunities are evaluated when they affect privacy. Capacitive proximity sensing has the advantage that, despite the capabilities offered by similar systems, it is difficult to derive privacy-threatening data when the sensor topology and processing model are unknown. Even though capacitive proximity sensing seems to offer privacy-

friendly features, we need to check whether people take this into account when selecting products. In other words, we should examine whether vehicle users value privacy-friendly features over other sensing systems. Public regulations for privacy by design can be circumvented by automakers, but customers' decisions about privacy-friendly systems cannot be circumvented. To prepare for the test of whether or not vehicle users value privacy-friendly features, three hypotheses are formulated to support the need for further integration of capacitive proximity sensing in vehicles. The hypotheses are based on related work addressing privacy threats from camera-based systems in Section 2.4.2 and analysis of camera systems versus capacitive proximity sensing in Section 6.1.3. Based on the privacy concerns identified for video surveillance, we state that video surveillance of drivers in vehicles raises privacy concerns for users. This leads to the first hypothesis:

> **Hypothesis I**: *If a vehicular human machine interface contains a camera which captures images of passengers, then people have privacy concerns about the vehicular human machine interface.*

As shown in Table 6.2, capacitive proximity sensing is a technology that enables similar functions for human machine interfaces in vehicles as camera systems. In addition, capacitive proximity sensors do not capture an image of the passengers. Therefore, a second hypothesis has emerged:

> **Hypothesis II**: *If a vehicular human machine interface is based on capacitive proximity sensing and does therefore not capture an image of passengers, then people have less privacy concerns about the vehicular human machine interface compared to camera-based systems*

Both hypotheses focus on the comparison between camera and capacitive proximity sensing. A direct preference, however, is not indicated. So, there is no correlation between the preference of capacitive proximity sensing versus camera-based systems. Hypothesis three is therefore formulated to account for direct user preference. The formulation of hypothesis III is as follows:

> **Hypothesis III**: *If a car user has to choose between camera-based vehicular human machine interfaces and capacitive proximity sensing-based vehicular human machine interfaces, then she or he will prefer the capacitive proximity sensing-based system*

## 6.2. Analysis of existing systems from the user's perspective

The perspective from law for different vehicular human machine interfaces was analyzed in Section 6.1. Because the analysis is based on considerations of law only, hypotheses were formulated to provide a basis for the assessment of the car user's voice. Based on those hypotheses, a questionnaire was designed in Section 3.2.2. The questionnaire is evaluated in this Section, beginning with Section 6.2.1. Section 6.2.1 presents the distribution of participants. It shows the total number of participants and the number of participants within the target group. Section 6.2.2 shows, subsequently, the visualized selections of the participants for each question. We discuss the selections of participants, the representativeness of the sample, and the significance of the results with respect to the hypotheses in Section 6.2.3

### 6.2.1. Participants

We now consider the participants who took part in the survey. Demographic information such as the age of the participants and their place of residence within Germany is presented. In order to collect the participants, the questionnaire is distributed through the personal and academic network of the project leaders. Additionally, a link is provided on various online platforms [Sur16, Abe19]. The distributed link remained active for a period of 84 days. During this period, a total of 302 completed questionnaires were collected. Participants are then

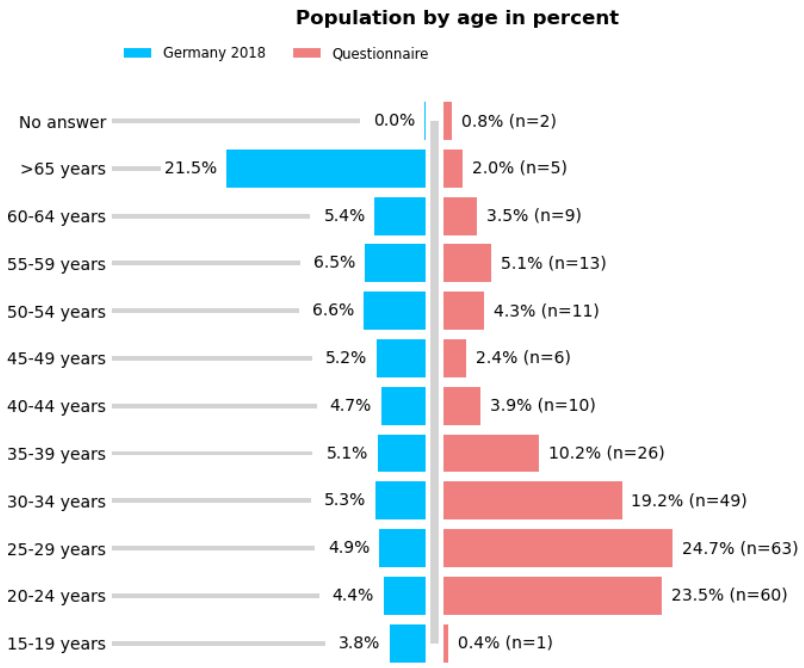



Figure 6.4.: Participants age distribution compared to German population [FK20c]

filtered to avoid outliers. They are filtered based on their speed. In other words, they are filtered based on how long it took respondents to complete the survey. According to Leiner [Lei19], an answer speed that is more than twice as fast as the median speed of all participants is suspicious and should be filtered. The speed filter is applied to all responders and the number of valid completed questionnaires is reduced to 260. 42 responders who are excluded responded more than twice as fast as the median response speed of the other participants. Within the remaining group of 260 participants, 109 were collected through the personal network. 14 were collected through the academic network. After reducing the risk for random responses, the target group is extracted from the respondents. The final questionnaires are filtered for German drivers. 257 participants live in Germany. Thus, the remaining group is reduced to 257. 255 of the German participants use a car more than once a year. The total number of respondents in the target group is therefore 255. Subsequent figures refer to this total number of participants in the target group.

To be able to check the demographics of the participants, they were asked to select their age category. They were able to divide themselves into a range of ages from 15 to over 65. Each group spanned five years. In preparation for assessing the representativeness of the sample, discussed in Section 6.2.3.1, the age distribution is compared with the age distribution of the target group. The age distribution of the participants is therefore compared with the age distribution in Germany in 2018 [Sta19]. The comparison is shown in Figure 6.4. As shown in Figure 6.4, the comparison is partly imbalanced. Germans aged 65 or over account for 21.5% of the population. This age group is represented by 2.0% (n=5) of participants in the survey. In contrast to this

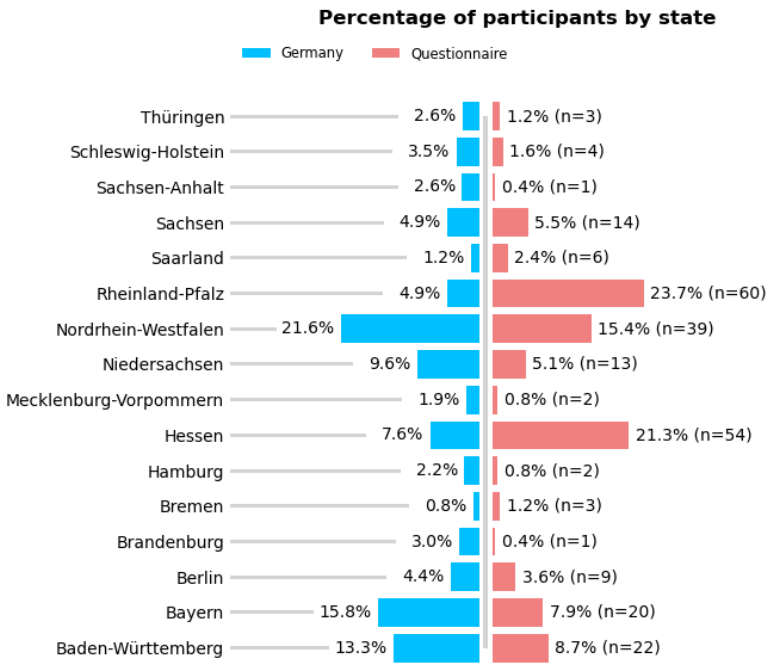



Figure 6.5.: Participants' state compared to German population [FK20c]

underrepresentation, participants in the 25 to 29 age group cover 24.7% (n=63) of all participants. Only 4.9% Germans are in this group.

In addition, participants are asked to select their federal state. In this way, the representativeness of the location, between the German population as of 2019 [Sta20a] and the questionnaire can be estimated. A comparison between the percentage of the population in Germany and the federal states is shown in Figure 6.5. The distribution of the participants' location is also shown. Rheinland-Pfalz covers 23.7% (n=60) of all participants. This exceeds the percentage of Germans living in Rheinland-Pfalz (4.9%). Similarly, Hessen covers 21.3% (n=54) while the percentage of Germans living in Hessen is 7.6%. On the other side, for example, only 7.9% (n=20) participants live in Bayern while 15.8% of the German population live there.

### 6.2.2. Participants' selections

The demographic characteristics of the participants in the target group were shown in Section 6.2.1. Now let's look at the participants' answers regarding privacy and their preferences. The analysis of the responses is also needed for the significance tests, in Section 6.2.3.2. Participants are asked to rate their privacy concerns towards cameras and capacitive proximity sensing using Likert-scaled questions. After the socio-demographic questions from Section 6.2.1, the questionnaire continues with a general question about privacy concerns about cameras and capacitive proximity sensing in vehicles. General means that the processing location is not specified. The selections of the participants are shown in Figure 6.6. As shown in Figure 6.6, both sensor types received

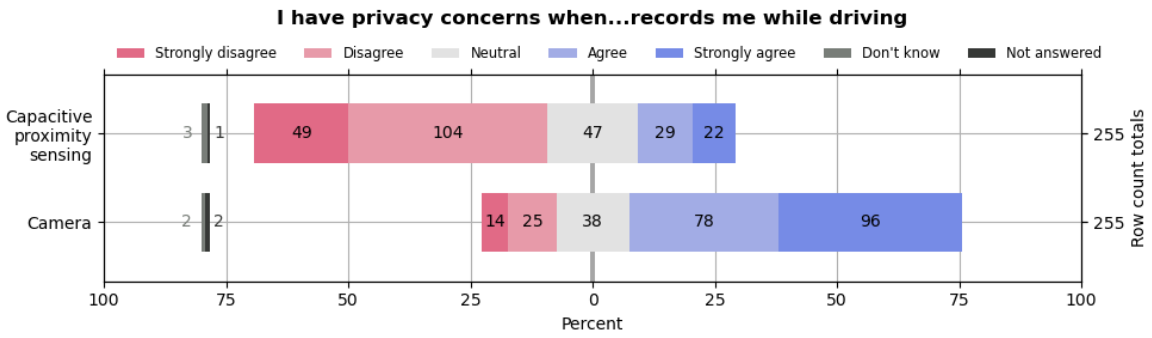



Figure 6.6.: General privacy concerns for the systems installed in vehicles [FK20c]

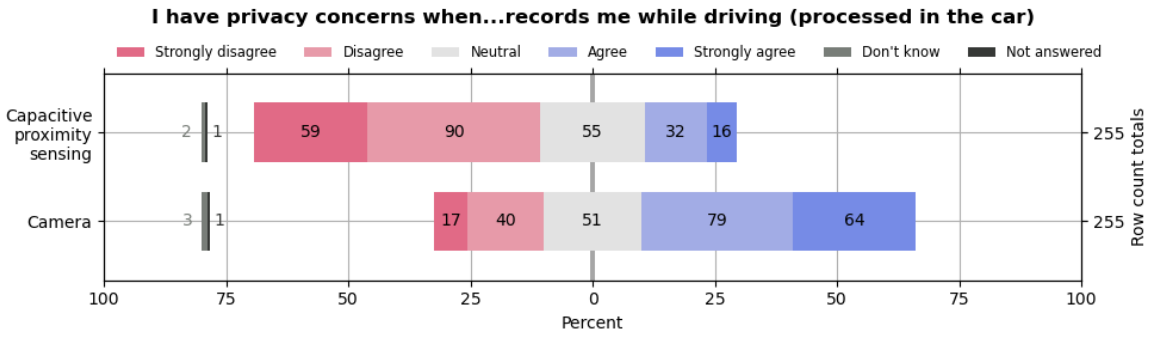



Figure 6.7.: Privacy concerns for the systems installed in vehicles and data is processed in the vehicle [FK20c]

approximately the same number in the neutral category. Privacy concerns about capacitive proximity sensors show a score of 47 in the neutral category, while privacy concerns about cameras show a score of 38. To compare the responses for both sensing systems, the answer categories are combined. Answers *"strongly agree"* and *"agree"* are combined to an agree group, and *"strongly disagree"* and *"disagree"* are combined to a disagree group. The relationship between the sensor systems can then be calculated. 68.2% (n=174) of participants agree that cameras cause privacy concerns when installed in vehicles. 20.0% (n=51) of participants agree that capacitive proximity sensing causes privacy concerns if installed in vehicles. The number of participants who have privacy concerns about cameras thus exceeds that of capacitive proximity sensing by a factor of 3.4.

The same question is asked again with the processing location specified. Participants are first asked to rate their privacy concerns about in-vehicle data processing. The choices made by the participants are shown in Figure 6.7. When the data is again grouped into agree and disagree, 56.1% (n=143) of participants agree that cameras cause privacy concerns when data is processed in the car. 18.8% (n=48) of participants agree that capacitive proximity sensing causes privacy concerns when data is processed in the car. The number of participants indicating privacy concerns about cameras exceeds the concerns about capacitive proximity sensors by about three times.

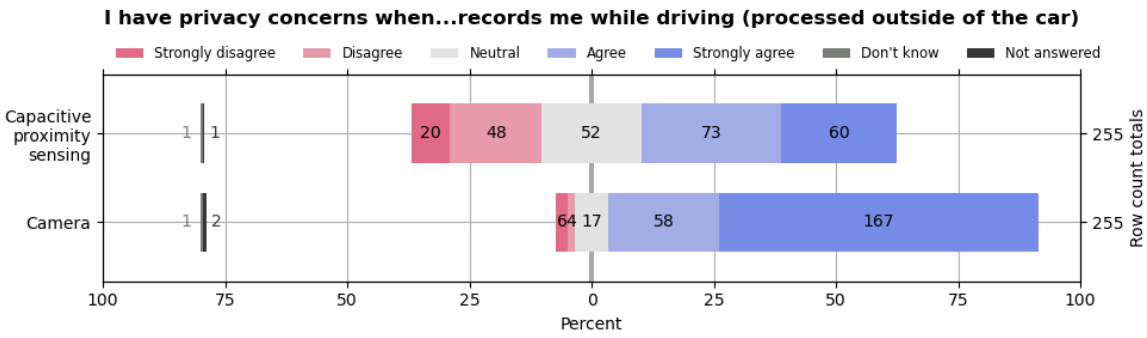



Figure 6.8.: Privacy concerns for the systems installed in vehicles and data is processed outside of the vehicle [FK20c]

Participants are then asked to rate their concerns about data privacy when the data is processed outside the vehicle (e.g., in a data center). The participants' responses are shown in Figure 6.8. 88.2% (n=225) of participants agree that cameras cause privacy concerns when the data is processed outside the vehicle. 52.2% (n=133) of participants agree that capacitive proximity sensing causes privacy concerns when data is processed outside the vehicle. The number of participants who have privacy concerns with cameras exceeds those with capacitive proximity sensors by 1.7 times.

To test participants' preferences between camera and capacitive proximity sensors, each question is accompanied by another question. Participants are asked to select the system that causes greater privacy concerns. Similar to the previous questions, the processing location is changed. Participants select the system that generally causes greater privacy concerns, then the system when the data is processed locally, and then the system when the data is processed outside the vehicle (e.g., in a data center). Figure 6.9 shows the selection for all three processing location specifications. In all scenarios, capacitive proximity sensing is selected by a few participants (2.0% (n=5), 0.8% (n=2), 0.8% (n=2)). Contrary to capacitive proximity sensing, the majority selects cameras as the most privacy concerns causing system (74.1% (n=189), 69.4% (n=177), 63.9% (n=163)). Even though capacitive proximity sensing is only directly selected by a few participants, it is included in the responses that state that people have great concerns for both systems. Great concerns for both systems remain almost steady at processing in general (10.2% (n=26)) and processing in the car (11.8% (n=30)). The great concerns for both systems increase up to 29.8% (n=76), if data is processed outside of the car. The associated distribution by age is shown in Figure 6.10 to assess the representativeness of the sample for different age groups.

To address the last hypothesis, participants are asked to name their preferred system, assuming that both systems work equally well. In addition, they are asked whether they would be willing to pay more for one of the systems. The participants answers are shown in Figure 6.11. 7.5% (n=19) of the participants prefer cameras as system for driver assistance systems. Moreover, 83.1% (n=212) of the participants prefer capacitive proximity sensing. Even though most participants prefer capacitive proximity sensing, only 38.0% (n=97) of the participants would pay more for the system. A large group of 41.2% (n=105) participants would be willing to pay the same for both systems.

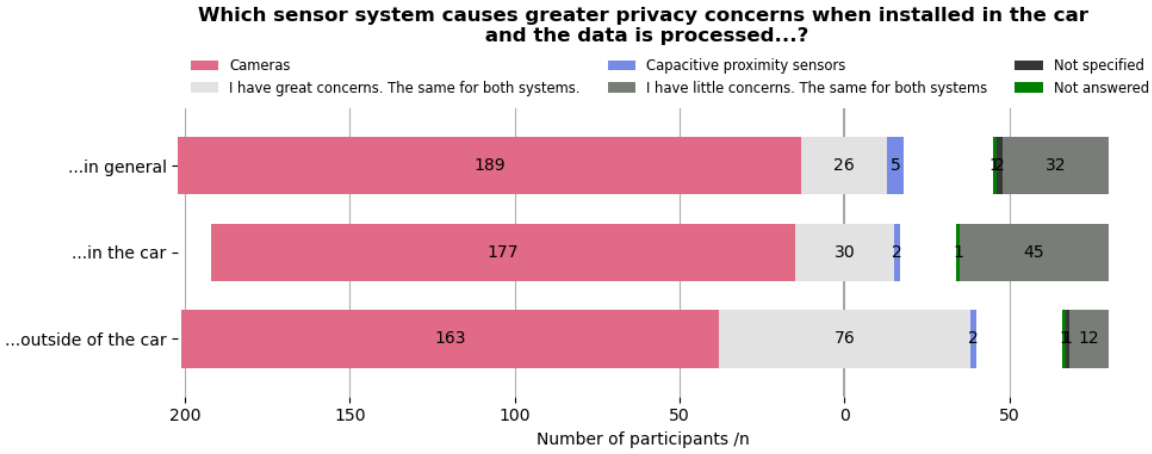



Figure 6.9.: Participants' selection of systems which cause greater privacy concerns [FK20c]

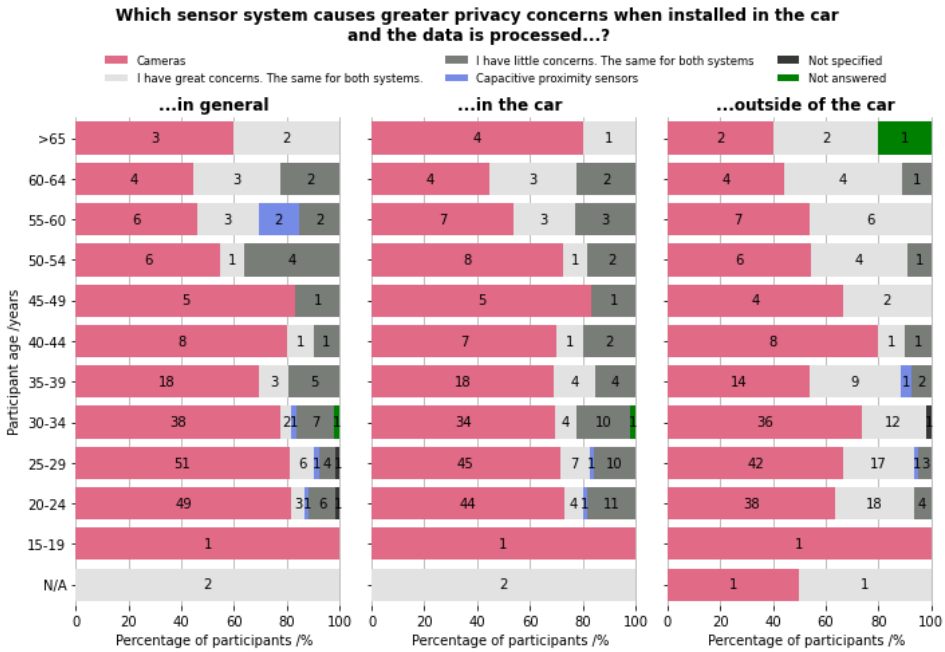



Figure 6.10.: Participants' selection of systems which cause greater privacy concerns by age group [FK20c]

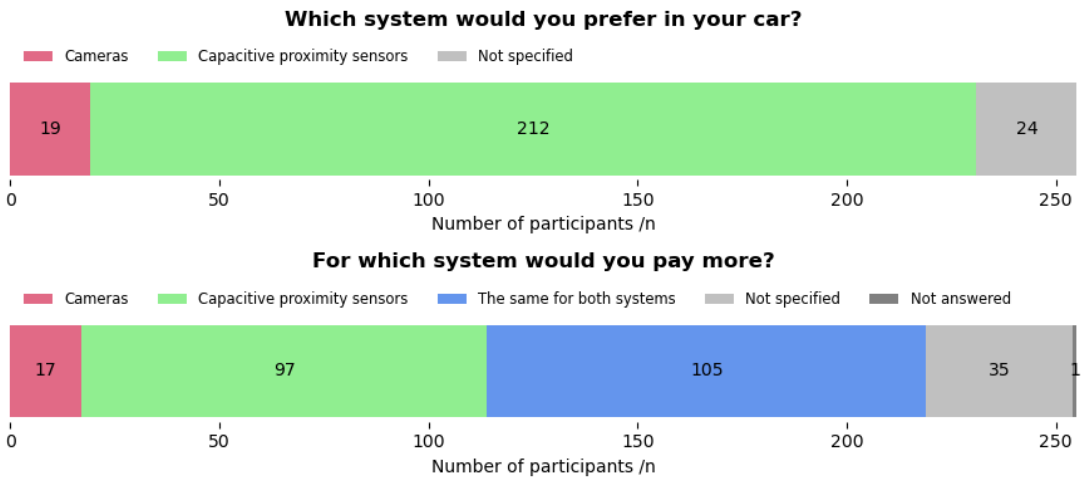



Figure 6.11.: The preferred system of participants and their willingness to pay more [FK20c]

### 6.2.3. Evaluation

Before we begin the evaluation, I provide comments here on the concept of the survey. Similar to many quantitative surveys, participants cannot provide feedback on the questions asked. Thus, it depends on the pretest and the design of the questions whether the collected data reflect the participants' opinion in an unbiased way. To avoid ambiguity, a pretest is conducted as described in Section 3.2.2.5. The pretest consists of 15 participants. This corresponds to about 5.9% of the recruited participants of the target group. Ambiguities may therefore not be completely ruled out. The survey aims to answer the hypotheses stated in Section 6.1.4. These hypotheses aim to compare cameras with capacitive proximity sensing. Neither the questionnaire nor the hypotheses consider the need for cameras in some systems. In addition, none of the hypotheses compare capacitive proximity sensors with other detection systems in the vehicle. Capacitive proximity sensors could raise additional privacy concerns if, for example, they replace simple push buttons.

#### 6.2.3.1. Representativeness of the sample

According to Mayer [May13, p. 60], representativeness is given if conclusions can be drawn about the population from the sample. The distribution of all relevant characteristics in the sample must therefore match the population. In summary, representativeness is a measure of whether the results of this survey can be generalized to all car users in Germany. We tried to recruit as many participants as possible. 123 of the participants were recruited through the private and academic network of the project staff. 51.8% (n=132) were thus recruited via online platforms. This is a largely balanced distribution. Nevertheless, all participants are gathered as convenience samples. The advantage of convenience samples is the low effort required to recruit participants. The disadvantage of this approach is that participants self-select. Participants may be motivated because they have a bias against privacy concerns or the automotive industry. Each participant must be able to open the link to the questionnaire on a device capable of displaying the questions. As a result, individuals without a device capable of displaying a website will not be able to participate in the survey.

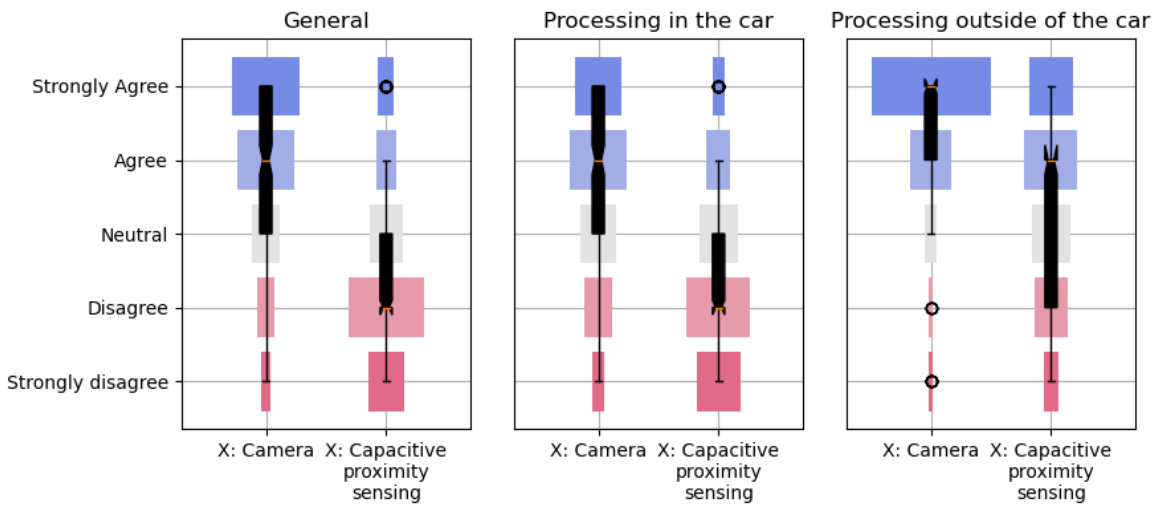



Figure 6.12.: I have privacy concerns when X records me while driving [FK20c]

Another issue occurs due to the definition of the target group. The survey aims to recruit German car users. According to Follmer et al. [FG19], every household in Germany owns more than one car on average. Even if not everyone in the household is a car user, the target group is probably very large. In fact, the number of questionnaire participants who are German and use a car more than once a year is about 99.2% of all German participants. Although the vast majority of all participants are German car users, the population distribution may not be represented by the participants. As shown in Figure 6.4, participants with an age between 20 and 39 years seem to be overrepresented. People with an age of more than 65 years are underrepresented. The results of this survey may therefore not represent all car users in Germany. Consequently, the results must be interpreted as an indication of people's preferences. In addition, the spatial distribution of participants is unbalanced in terms of the proportion of Germans living in certain federal states. As shown in Figure 6.5, states like Hessen and Rheinland-Pfalz cover the majority of the participants' locations. Contrary to this, those two states are not even in the top three of German states with the highest population. In fact, a state like Bayern consists of 15.8% of the population of Germany. The percentage of recruited participants from Bayern is only 7.9% (n=20). To enable the assessment of the representativeness for different age groups, Figure 6.10 is added. In this figure, one can see the participant count and the selections of the participants disaggregated by age groups.

#### 6.2.3.2. Significance testing

As shown in Section 6.2.3.1, results of the hypotheses tests may not be representative for all age groups. Nonetheless, statistical tests are conducted using the gathered data. Hypotheses are therefore checked for the sample. The distribution of the Likert-scaled questions is shown in Figure 6.12. In this figure, the colored bars refer to the value distribution in Figures 6.8, 6.7 and 6.6. Additionally, a boxplot for each question is added. The notch in each black box shows the median value of the sample. Top and bottom of the thick black boxes show the first and third quartile of the data. Using the data presented in Figure 6.12, a one sample T-Test [BS10] is conducted for Hypothesis H1 (Section 6.1.4). H1 is tested against a null hypothesis. The null hypothesis states that people

| Processing location | Critical Value | t | σ |
|---|---|---|---|
| General | 2.3 | 11.5 | 1.2 |
| In the car | 2.3 | 6.9 | 1.2 |
| Outside of the car | 2.3 | 27.1 | 0.9 |

Table 6.3.: Hypothesis H1 significance test

have no or neutral privacy concerns when a camera is installed in their car. Therefore, this is a one-sided test. The expected mean value $\mu_0$ for the null hypothesis is set to three on the presented Likert-scaled questions. The results of this significance test are shown in Table 6.3. A significance level $\alpha = 0.01$ is used. Depending on the relationship between t and the critical value, the hypothesis can be evaluated. If the t value is greater than the critical value, the null hypothesis can be rejected. The critical value is a threshold value that indicates the transition from keeping and rejecting the null hypothesis. In this case, the t-value is greater than the critical value for all tests. H0 can be rejected for the sample.

After the first hypothesis is checked for the sample, we can move over to the second hypothesis. The questions *"When data of you is recorded while driving and processed (X), which sensor system causes greater privacy concerns? (Where X stands for: in general, in the car, outside of the car)"* addresses hypothesis H2. H2 states that people have lower privacy concerns when capacitive proximity sensing is used in vehicles compared to cameras. The null hypothesis is that people do not have lower privacy concerns when capacitive proximity sensing is used in vehicles compared to cameras. We then consider the answers to this question as follows:

- Yes: Answers contribute to H2
  - Answer: Cameras
- No: Answers contribute to null hypothesis
  - Answer: Capacitive proximity sensors
  - Answer: I have great concerns. The same for both systems
  - Answer: I have little concerns. The same for both systems

The percentage of participants which relate to categories "Yes" or "No" are shown in Figure 6.13. In addition, the confidence interval for the selections is shown as vertical black lines. The confidence interval is a range that indicates plausible possible true values. To reject the null hypothesis, the lower bound of the confidence interval for "Yes" must be greater than 50%. If 50% were included in the confidence interval, this value would be plausible, meaning that no preference for "Yes" or "No" would be detected. In all three cases, general processing, in-car processing, and out-of-car processing, the confidence intervals are exclusive for the "Yes" and "No" groups. This indicates a rejection of the null hypothesis. This is also supported by the fact that the lower confidence limit of "Yes" is greater than 50%. However, when the data are processed outside the car, the confidence intervals converge. The lower bound of the confidence interval for "Yes" is only 6.7% above 50%. Nevertheless, the null hypothesis can be rejected for the sample.

After hypothesis H2 is processed, the next considered hypothesis is H3. The question *"Under the condition that both systems work equally well, which sensors would you prefer in a driver assistance system?"* addresses hypothesis H3. H3 states that people who have a choice between using a camera or capacitive proximity sensors in driver assistance systems will choose capacitive proximity sensors. The null hypothesis states that people do not have a preference for capacitive proximity sensors, and therefore there is no significant difference between the number of people who choose cameras or capacitive proximity sensors. The answers to this question are grouped together:

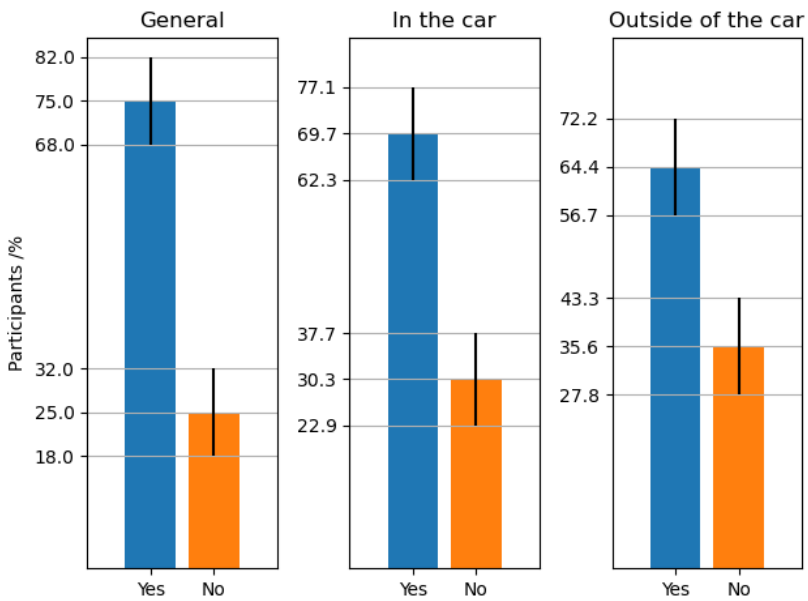



Figure 6.13.: Confidence intervals; significance level $\alpha = 0.01$ [FK20c]

- Yes: Answers contribute to H3
  - Answer: Capacitive proximity sensors
- No: Answers contribute to null hypothesis
  - Answer: Cameras

Based on this grouping of responses, the percentage of participants responding to the "Yes" or "No" categories is shown in Figure 6.14, on the left. Additionally, the confidence interval for the selection is shown as vertical black lines. The confidence intervals are exclusive for the "Yes" and "No" groups. This indicates the rejection of the null hypothesis. Additionally, the result of question *"Assuming that both systems work equally well, for which sensors in a driver assistance system would you pay more?"* is shown on the right of Figure 6.14. The question aims to formulate a fourth Hypothesis: *"If a car user has to choose between camera-based vehicular human machine interfaces and capacitive proximity sensing-based vehicular human machine interfaces, then she or he will prefer the capacitive proximity sensing-based system even if she or he has to pay more."*. In this case, the null hypothesis is that people would not pay more or the same amount of money if given the choice. Similar to the previous tests, the response categories are grouped. The "Yes" group supports the alternative hypothesis, and the "No" group supports the null hypothesis.

- Yes: Answers contribute to alternative hypothesis
  - Answer: Capacitive proximity sensors
- No: Answers contribute to null hypothesis
  - Answer: Cameras
  - Answer: The same for both systems

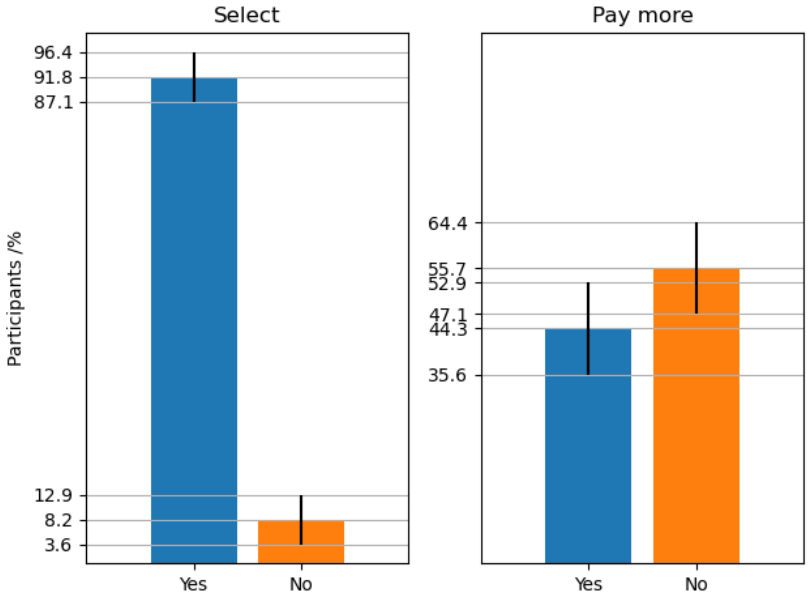



Figure 6.14.: Confidence intervals; significance level: $\alpha = 0.01$ [FK20c]

As shown in Figure 6.14 on the right, the alternative hypothesis is not supported by the sample. Nevertheless, the question and the hypothesis are categorical. A hypothesis with intervals on how much people would be willing to pay more could lead to different results. Therefore, the question would need to be converted into a series of questions to determine the amount of money a participant would be willing to pay for the systems.

## 6.3. Discussion

The aim of Chapter 6 is to find evidence for research question RQ3: *Can capacitive proximity sensing contribute to the acceptance of vehicular human machine interfaces with regard to privacy concerns?* Due to possible differences between the perspective of the user and regulations, the research question is split into two parts. We will discuss in Section 6.3 the relation between the presented information and findings of Chapter 6 with RQ3. Each element of the research question is first discussed separately. The findings that can be derived are then linked and generalized so that any unresolved parts of the research question can be revealed. We start with the regulation part and recapture the motivation for Chapter 6. The necessity of privacy preserving systems is presented in Section 3.2.1 and reviewed in related work (Section 2.4). When human machine interfaces in vehicles collect more information than necessary, it can lead to privacy issues. A system could be hacked, or manufacturers could pass on information to data-collecting third-party companies or even use the data themselves. Threats to privacy from in-vehicle human machine interfaces could therefore lower system adoption. Capacitive proximity sensing is often said to preserve or better protect privacy compared to camera-based systems [TLIL17, AKA*17, YZH*20, AKK*15, MKMF*17, FDKK20, NSR*15, RJBK18]. It appears that research question RQ3 regarding the comparison of capacitive proximity sensing with other sensing systems has already been answered. Nevertheless,

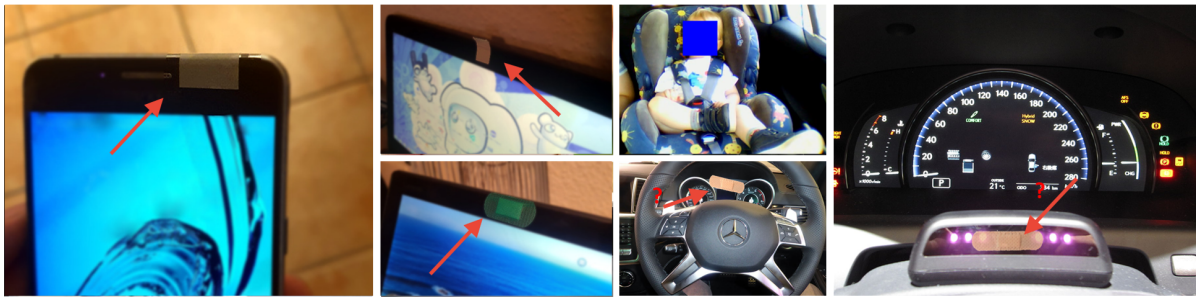


Figure 6.15.: People cover their web cams. Will they cover vehicle cameras in the future? [Tok13, Fan09]

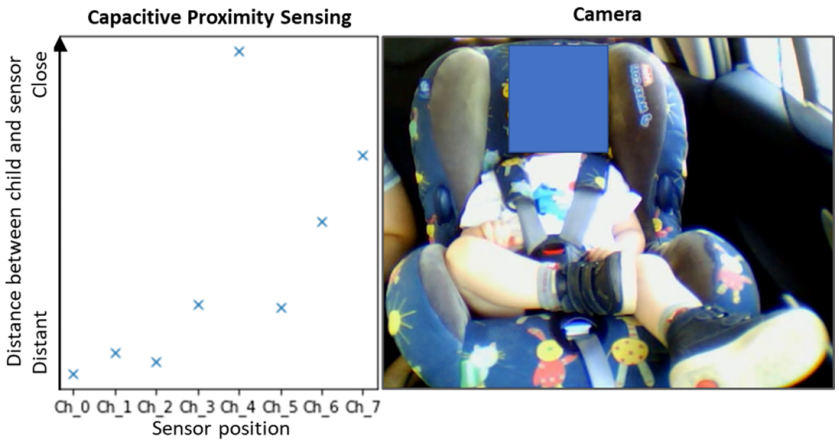



Figure 6.16.: Capacitive proximity sensing and related video data [FK20c]

no studies were found to support these statements. For this reason, the analysis of existing systems regarding research question RQ3 is necessary. An analysis of existing systems and potential privacy intrusions based on regulations is therefore conducted in Section 6.1.3. Before evidence for privacy threats and thereby RQ3 can be found, a definition for privacy that can be applied in the examination of systems has to be found. A general definition of causes for privacy concerns is therefore derived from the GDPR and presented in Section 3.2.1. In particular, privacy concerns are raised whether personal, biometric or genetic data can be captured or whether user profiles can be derived from the usage of the system.

Based on this definition of privacy, several vehicular human machine interface systems are presented and analyzed. They are comprised of camera- and/or microphone-based sensors as shown in Section 6.1.1. Similar systems based on capacitive proximity sensing are presented in Section 6.1.2. The concept presented in Section 3.2.1 is applied for the analysis of those systems. According to this analysis, the assignment of the attribute data protection compliant, to capacitive proximity sensing technology in vehicles, can be confirmed to a limited extent with regard to the regulations of the European Union. In particular, the information within a driver image or microphone recording, may reveal a variety of targets. Systems based on cameras or microphones, originally intended to capture driver gestures or fatigue, can provide information for profiling or extraction of biometric or health data. They may therefore come into conflict with the "privacy by design" paradigm of the GDPR. Nonetheless, it is shown in Section 6.1.3 that capacitive proximity sensing-based systems show the ability to identify people. They can therefore also interfere with privacy. Nonetheless, capacitive proximity sensing data without further information can barely be used to derive information. Even though target information, like the identity, may be encoded within data, the extraction is cumbersome. To emphasize this condition, capacitive proximity sensing data is shown exemplary in Figure 6.16 on the left. The corresponding image taken by an in-vehicle camera of this sample is shown on the right of Figure 6.16. The system is designed to track child movements in a baby seat as shown in Section 4.2. The captured image reveals a lot of information that is contrary to data protection. For example, biometric information could be extracted. Information from capacitive proximity sensing is quite useless without the topology of the sensors and additional labels. The approach presented in this example has been applied to several human machine interfaces in vehicles. In particular, due to the in Section 3.2.1 presented metric "Purpose - Opportunity - Difference", possible privacy threats causing applications can be identified. Due to the "Purpose - Opportunity - Difference" of camera-based systems, it is questionable if they still follow paradigm privacy by design.

This leads to the second question we discuss in Chapter 6. The actual judgment on whether sensor systems in vehicles comply with Privacy by Design must be made by jurisdiction. Nonetheless, in addition to regulations, the voice of potential vehicle customers can influence manufacturers' design decisions. If vehicle users value privacy by design, manufacturers would be encouraged to reconsider the use of cameras or microphones. This resulted in three hypotheses for a questionnaire, which are presented in Section 6.1.4. The hypotheses are strictly designed to reveal user preferences regarding capacitive proximity sensing and cameras. Further comparisons to other sensor systems are not included. In addition to the hypotheses, research question RQ3 also arose from existing circumstances discovered in related work. Specifically, related research helped to measure people's privacy concerns about future cars, especially with respect to autonomous vehicles, as shown in Section 2.4.1. People are asked if they have privacy concerns about data being collected when using networked autonomous vehicles. Yet, there has been no specific analysis of privacy concerns about an existing sensor system in cars: the camera. Outside the automotive domain, related work has already discovered people's privacy concerns about camera-based systems in residential environments with assistants. It may be that people are unaware of alternatives to camera-based assistance systems such as capacitive proximity sensing in vehicles. In order to measure the privacy concerns of people concerning cameras in vehicles, and their preference of capacitive proximity sensing compared to cameras the concept presented in Section 3.2.2 is applied. It consists of three hypotheses that were tested in a survey, with German car users as the target group. 302 participants completed

the questionnaire. The responses were filtered by speed. Randomly answered questionnaires were filtered. More than 250 samples of the target group were then collected. Significance tests were conducted to find evidence for the hypotheses and thus for research question RQ3. Subsequently, hypotheses H1, H2, and H3 were tested and accepted for the sample. Significance tests of hypothesis H2 can be accepted for general use, in-car data processing, and out-of-car processing. However, for out-of-car data processing, people seem to engage with both systems. Hence, the hypothesis test for H2 is less significant for the sample in this case compared to processing in general and inside of the car (concerning a significance level of $\alpha = 0.01$). In summary, this means that people of the sample have privacy concerns if cameras are used in vehicular human machine interfaces (H1). People of the sample have less privacy concerns if capacitive proximity sensing is used compared to cameras (H2). Subsequently, a participant in the target group would choose capacitive proximity sensors instead of cameras for their in-vehicle human machine interface, assuming that both systems perform equally well (H3). By asking participants if they would even pay more for capacitive proximity sensing technology, a fourth hypothesis was to be uncovered. However, participants' responses to the corresponding question do not indicate that people would pay more. A corresponding hypothesis cannot be rejected based on this sample because the amount of money people would be willing to pay would have to be determined.

Based on these results for research question RQ3, we can now conclude what has been answered and what is still open for future research. The first part of RQ3 relates to the legal perspective. Capacitive proximity sensors seem to show less privacy threats compared to other human machine interfaces in vehicles based on cameras or microphones. This is an indication that the use of capacitive proximity sensing could increase the acceptance of human machine interfaces in vehicles with respect to the privacy required in RQ3. Nevertheless, the selection of in-vehicle human machine interfaces focuses on cameras and microphones. Hence, the evidence for RQ3 must be specified to: Capacitive proximity sensing can contribute to the acceptance, compared to camera or microphone-based systems. The analysis based on regulations can only increase the acceptance when manufacturers are forced to use other systems than cameras or if the car user values accordance of the system with regulations. Whether the car user values accordance of the system with regulations is also a matter of RQ3. The formulated hypotheses that are checked in Section 6.2, address the preference of the user and her or his subjective privacy concerns towards cameras and capacitive proximity sensors. They therefore directly contribute to RQ3 from the user's point of view. The comparison is nevertheless only based on cameras and capacitive proximity sensors. As a result, the answer to RQ3 must be narrowed down to: Yes, capacitive proximity sensing can contribute to the privacy acceptance of human machine interfaces in vehicles compared to camera-based systems. To generalize this answer, capacitive proximity sensing would need to be compared with other sensing systems or the user's perception would need to be surveyed. Even though the presented survey supports the validity of the hypotheses for the sample, the survey shows an imbalanced age and location distribution compared to Germany. The hypotheses need to be tested in a more representative study without self-selection and recruitment based on the demographic distribution in Germany. Each hypothesis could even be tested in a separate survey. This could further improve the evidence for research question RQ3. Another open issue for research question RQ3 is why cameras might be preferred by the manufacturer. Capacitive proximity sensing is a sensor system already used in automotive applications. Nevertheless, manufacturers seem to prefer camera-based solutions. This thesis did not investigate the reasons for this fact. The aim was to investigate how manufacturers go about selecting sensors for the human machine interface in vehicles in order to find out what weight data protection has for the manufacturers. Subsequently, one could evaluate the decision of manufacturers to choose privacy-sensitive sensor systems for gesture recognition. This does not necessarily contribute to the question of user acceptance, but it could reveal why capacitive proximity sensing is not on the minds of users, who might thus initially demand its use. In particular, the maturity of capacitive proximity sensing in vehicles would need to be demonstrated. In addition to the questionnaire and analysis, it is recognized that people take action when they do not show great acceptance of a system. As can be seen in Figure 6.15, people are already obscuring their cameras in devices

around them. They obscure the cameras of notebooks, cell phones and tablets. By working on this thesis, another question arose: will people start covering up vehicle cameras in the future. This question is especially interesting when people do not have the choice of having a vehicle with or without a camera. This situation could become real in car sharing situations. We can be curious to see if obscuring vehicle cameras will be seen more frequently in the future.

# 7. Conclusions and future work

With the conclusion of the chapter on privacy, we have examined the final building block of this thesis, which will now be concluded. For this purpose, this chapter is structured in such a way that first all the building blocks of the thesis, the research questions, are recapitulated. The contributions to these questions consist of the individual chapters of this thesis. Therefore, a detailed look at related topics is important. After summarizing the related works, the concept of this paper is summarized that was written based on the study of relevant works. Based on the concepts found, we can summarize the individual contributions of the implementations related to human machine interfaces, interaction, and the influence of privacy in vehicles. Limitations of this thesis and open questions are then presented. So, we now briefly take a look at the content of these questions. Research question RQ1 addresses human machine interfaces without interaction in vehicles. The aim is to show how capacitive proximity sensors can be applied in existing vehicle structures to improve human machine interfaces in vehicles. Research question RQ2 adds the modality of interaction but keeps the constraints. It is important to keep in mind that mainly technical views of capacitive proximity sensing in vehicles are addressed by research questions RQ1 and RQ2. Research question RQ3 relates to the acceptance of human machine interfaces in vehicles. The aim is to investigate whether the use of capacitive proximity sensors can influence this. The attribute privacy-preserving is investigated here. The research questions are now listed:

- RQ1: How can we use existing vehicle structures to enhance or substitute vehicular human machine interfaces using capacitive proximity sensing?
- RQ2: How can we use existing vehicle structures to provide new ways of human computer interaction using capacitive proximity sensing?
- RQ3: Can capacitive proximity sensing contribute to the acceptance of vehicular human machine interfaces with regard to privacy concerns?

In order to present the origin of the contributions to these questions, it is necessary that applications and the physical conditions are introduced. In order to make the operation of capacitive proximity sensors understandable, an overview of capacitive proximity sensing and human machine interfaces in vehicles is given. It has been shown that with capacitive proximity sensors it is possible to measure changes in the electric field in the vicinity of the sensors. Since the movement of people affects the electric field, these motions are included in the outputs of the capacitive proximity sensors. The application of capacitive proximity sensors is additionally presented. Considerations for the selected material for sensing electrodes and properties such as resolution and sensing range are presented in particular. Existing applications for in-vehicle and off-vehicle use have also been shown. Capacitive proximity sensors are integrated, for example, into armrests in the vehicle to provide gesture control for the driver. They are also used, for example, to detect the position of child seats in vehicles. In addition to investigating applications of human machine interfaces in terms of the technical side, privacy concerns of people towards vehicle-based human machine interfaces and certain sensor systems in their environment have also been presented. It has been found that in related research, cameras are mainly studied in capturing users' privacy concerns. Related work also shows that remarkable capabilities of capacitive proximity sensors are being demonstrated outside the automotive field. Integrated into furniture, they have the ability to assess a variety of human symptoms and signs that could have useful application in vehicles. A concept was therefore created to show how these sensors could be usefully applied in vehicles.

The concept consists of ten steps that are considered important for the development of a human machine interface in vehicles based on capacitive proximity sensors. The first steps show how an idea for an application can arise. This involves evaluating issues and linking them to potentially measurable human emissions. Next, a vehicle structure for mounting the capacitive proximity sensors is selected so that capacitive proximity sensors can be integrated invisibly. Ways to develop and evaluate these applications are then presented. In particular, it was shown how data can be labeled and how a sensor topology can be developed and implemented within the vehicle structure. Coverage of privacy concerns in relation to the law and user perspectives is shown. A metric for assessing privacy threats is presented. The difference between the purpose of an application and the given capabilities, in particular, can indicate privacy threats. A questionnaire is also designed to assess user perceptions of privacy in relation to cameras and capacitive proximity sensing in vehicles.

## 7.1. Vehicular human machine interfaces with and without interaction

Now that the concepts for answering the research questions have been defined, we can move on to concrete implementations of the concepts. We begin with research question RQ1. To find evidence for this question, two monitoring devices have been developed. Both devices are based solely on capacitive proximity sensors and are integrated into existing vehicle structures. Capacitive proximity sensors are integrated into a driver's seat and a child's seat. The sensors are therefore invisible to the monitored subject. It has also been shown that these invisibly integrated sensors can detect a variety of different symptoms and signs from drivers or passengers. Processing methods for inferring symptoms of attention such as nodding, yawning, and gazing are evaluated, as well as a method for assisted driver seat adjustment. In addition, the child seat application monitors presence, current sleep state and head accelerations to prevent injuries. Attempts are also made to detect the heart rate of a child in a child seat. So, it is explained how capacitive proximity sensing can be used in vehicles to develop useful applications. By implementing all processing methods in prototypes and subsequent user studies, the performance of capacitive proximity sensing-based systems has been evaluated. The applications in this thesis further demonstrate the limitations of capacitive proximity sensing. Human emissions such as heart rate, in particular, are difficult to detect. The limitations demonstrated nonetheless also contribute to research question RQ1, as they can highlight where capacitive proximity sensing may not be the best choice for the specific measure in an in-vehicle human machine interface. It is thereby shown how two existing vehicle structures are used to enhance or substitute existing vehicular human machine interfaces to form significant applications for a proof of concept.

In addition to RQ1, the same concept is applied in RQ2, but extended to meet requirements for natural interaction in vehicles. In particular, guidelines for natural interaction are included. Using this concept, three applications for human machine interaction in vehicles have been developed. Two applications are based on driver hand tracking, while one application is based on foot posture. Existing vehicle structures are used for a new authentication mechanism in vehicles, a new type of head-up display control, and enabling interaction with a mostly unnoticed entity, the driver's feet. The use of existing vehicle structures with capacitive proximity sensing gave promising results. Hand and foot tracking is enabled with good performance based on the steering wheel and the driver's legroom equipped with capacitive proximity sensors. The actual hand or foot tracking is only one capability, but by applying the concept, meaningful applications are created. This demonstrates a new way of authentication in vehicles. Authentication is based on free hand gestures that can be freely exercised by the driver. Fundamental problems of existing authentication mechanisms such as the immutability of biometric data or the guessing of passwords through touch-based interaction are thus addressed. It was also shown how deictic gestures of the driver can be integrated into the control of head-up displays. Based on the assumption that the driving environment can be sufficiently segmented, two interaction concepts for deictic gestures in head-up

displays were presented. In addition to hand gestures, foot tracking was used for a set of four gestures in this thesis. In addition to the set of four deictic gestures, it has been shown that information about the behavior of the feet can indicate driver states.

In general, five applications have been examined for research questions RQ1 and RQ2. Each application is based on capacitive proximity sensing. It was shown how existing vehicle structures can be used for capacitive proximity sensing to measure symptoms and signs of the human body. In these applications, physiological states of the human body such as sleep state, yawning, nodding, heart rate, position of hand, foot, head, and arms can be detected. In addition, each measurement was put into a meaningful application, creating new opportunities for interaction or interfaces in vehicles. All applications were implemented in a prototype. Subsequently, each application was evaluated in user studies. The range of capabilities of capacitive proximity sensors in the automotive sector has thus been expanded. They are therefore no longer used as simple non-contact switches in vehicles, but can represent a significant extension or replacement of other sensor systems. All applications were developed with invisibly integrated sensors. Therefore, the applications are unobtrusive. Nevertheless, each provided application answers the research questions RQ1 and RQ2 only with limitations. All applications except the improved child seat were tested under laboratory conditions. More knowledge needs to be gathered as the proposed applications mature. Each application has to be installed in vehicles. This will require further testing under changing environmental conditions. The set of test subjects must also be expanded.

## 7.2. Privacy preservation and the user's voice

In addition to these applications contributing to RQ1 and RQ2, related work often finds that privacy-friendly applications can be developed using capacitive proximity sensing. Cameras are commonly used in in-vehicle human machine interfaces and can capture privacy-sensitive data due to their ability to capture facial images, for example. Capacitive proximity sensors cannot do this and therefore appear to be more privacy protective. Therefore, the statement that capacitive proximity sensing is privacy-compliant was investigated. To analyze this statement, several existing and already developed human machine interfaces in vehicles were examined. Data protection in relation to the GDPR was considered. This includes data that reveals any information about physical, physiological, biometric, and other personal data that can be associated with an individual. It has been shown how to identify potential privacy threats that arise as established sensor technologies mature. In general, the conclusion of this approach is that if data is collected from a sensor system that may reveal further information as needed to perform the application, and the further information conflicts with privacy, this may indicate privacy concerns for the system being analyzed. Based on this approach, it has been identified that capacitive proximity sensing has less privacy compromising mechanisms compared to, for example, cameras. In particular, camera-based systems were found to capture more information than necessary. Nevertheless, privacy concerns may arise from capacitive proximity sensors, as they can also be used to retrieve information such as the user's identity. However, deriving additional information from capacitive proximity sensing data from systems that are not designed to retrieve this information was found to be cumbersome. It is therefore concluded that privacy-friendly systems increase the acceptance of human machine interfaces in vehicles. Capacitive proximity sensors are assumed to have fewer privacy concerns. This provides evidence for RQ3 that capacitive proximity sensors may increase the acceptance of human machine interfaces in vehicles, if these interfaces are based on capacitive proximity sensors. Nevertheless, only a subset of sensors was investigated for research question RQ3. The evidence is also based on the current circumstance that it is cumbersome to derive additional information from solely capacitive proximity sensing data, while further information can be easily derived from, e.g., images. Thus, it is a snapshot of the current state. Should capacitive proximity sensing be widely used as a basis for human machine interfaces in vehicles, the interest in these sensor systems as a basis for deriving further privacy-

prone information could change. The data from capacitive proximity sensing could then be a basis for further data protection-related information in the future.

A second perspective was additionally investigated for research question RQ3. This perspective is based on the user's perception of privacy in human machine interfaces in vehicles. It has been investigated what people think about the use of cameras and capacitive proximity sensors in vehicles in terms of privacy. For this purpose, a questionnaire was designed in this thesis. The distribution of the questionnaire resulted in more than 250 valid responders belonging to the target group. The target group is German vehicle users. Based on the questionnaire, it can be seen that the people in the sample have privacy concerns about cameras used in vehicles. Furthermore, the individuals in the sample prefer capacitive proximity sensing as the basis for human machine interfaces in vehicles compared to camera-based systems. This provides evidence for research question RQ3 that capacitive proximity sensing can increase the adoption of human machine interfaces in vehicles with respect to privacy concerns. Nevertheless, only cameras and capacitive proximity sensors were compared in the questionnaire. It is therefore not assessed whether people prefer capacitive proximity sensors compared to other sensor systems. Besides the limitation of the investigated sensor systems, the target group is also limited to German car drivers. So, the results of this questionnaire cannot be generalized to other countries. Furthermore, the sample surveyed shows an imbalance in the age distribution compared to Germany.

## 7.3. Benefits, limitations and future work

Based on these contributions, benefit for research can be stated that results from this thesis. The concept presented can be used to incorporate capacitive proximity sensing into considerations for future in-vehicle human machine interfaces. The concept, in particular, shows a way to generate useful applications in vehicles. It was shown how capacitive proximity sensors can be unobtrusively integrated into existing vehicle structures for interfaces and interaction and how their data can be processed. By developing real applications, the implementation of applications in vehicles can be observed from scratch. In particular, the labeling of capacitive proximity sensing data is crucial. Therefore, several labeling options are provided that can be applied in future research. Another benefit comes from the specific applications developed in this thesis. For example, when researchers are working on monitoring concepts for vehicles, this thesis provides a basis for incorporating capacitive proximity sensing so that, for example, a more robust multimodal interface can be formed. Based on this thesis, it is already possible to identify specific human emissions that can be tracked. Emissions of this thesis are part of driver monitoring such as nodding, yawning, staring, suspicious steering movements, body measurements or presence. Emissions of this thesis are used for child monitoring through, for example, head movement, state of consciousness, presence, and heart rate detection, or they are part of gesture recognition such as hand or foot tracking. In addition to the technical considerations, it has been shown that capacitive proximity sensing seems to better protect privacy compared to camera-based systems. Therefore, this attribute can be assigned with higher confidence for future applications based on capacitive proximity sensing.

Even though the results are promising, there are limitations. Only five applications were studied in this thesis. All but one of the applications were evaluated under laboratory conditions. Therefore, the question of how existing vehicle structures can be used is only answered in terms of a proof of concept. Further evidence for these questions needs to be collected when conducting real tests in the context of long-term measurements. In addition, the evaluation showed that most processing algorithms require a variety of data from different users, but, for example, the extended child seat evaluations only collected data from one subject. Therefore, it is unclear whether the designed processing models generalize well to additional subjects. Another limitation arose from the use of benchmarking in the concept. Benchmarking is designed to select capacitive proximity sensors only if they are the best sensing system for the application. Some metrics of the benchmarking process, however,

are based on assumptions. The selection process may therefore be biased by the developer. Even though the metrics have been adjusted in this thesis, there are still metrics such as obtrusiveness that are not measurable. It is already suggested that such a metric could be evaluated in a customer study. In this thesis, an attempt was made to prove the metric obtrusiveness specifically with respect to privacy. Although more than 250 German car users responded, this study was conducted primarily to gain further hypothesis information. It is found that individuals in the sample prefer capacitive proximity sensors over cameras in vehicles. However, due to the exploratory nature, this was only found for the sample. Due to imbalances in the age distribution, this cannot be generalized. A more representative study will therefore need to be conducted in future work.

Benefits and limitations also point to future work. It was shown which parts of the research questions still need to be investigated. For example, it was shown how capacitive proximity sensing can be used in vehicles for interaction and interfaces. Nevertheless, future work needs to further develop and evaluate the presented applications. In particular, long-term measurements can provide further insight into the limitations and use of these sensors in vehicles. In addition, further properties of capacitive proximity sensing need to be analyzed. The actual design impact when these sensors are used, in particular, needs to be evaluated. It is still an assumption that invisible integration will have less of an impact on the design. Advantages and disadvantages of using capacitive proximity sensors for interior design should therefore be investigated. The fusion of capacitive proximity sensors with other sensing devices in vehicles could provide further and more robust opportunities to increase safety and comfort for vehicle users. Multimodal interfaces and interaction devices should therefore be investigated with the inclusion of capacitive proximity sensing. In this way, a more natural interaction is expected. In addition to the actual use of capacitive proximity sensing, we can be curious to see if the privacy-compliant behavior of drivers can be monitored in the future. It will be interesting to see if drivers will cover their cameras in the vehicle, similar to the standard cameras built into computers, to avoid being recorded without them wanting to.

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# A. Publications

**2020** **Privacy by Design: Survey on Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces** (Sebastian Frank, Arjan Kuijper) In Computer Science in Cars Symposium, CSCS '20, Association for Computing Machinery (New York, NY, USA, 2020), doi: 10.1145/3385958.3430474

**2020** **NannyCaps – Monitoring Child Conditions and Activity in Automotive Applications Using Capacitive Proximity Sensing** (Sebastian Frank, Arjan Kuijper) In HCI International 2020 – Late Breaking Papers: Digital Human Modeling and Ergonomics, Mobility and Intelligent Environments, Stephanidis C., Duffy V. G., Streitz N., Konomi S., Krömker H., (Eds.), Springer International Publishing (Cham, 2020), pp. 67–82, doi: 10.1007/978-3-030-59987-4_6

**2020** **Privacy by Design: Analysis of Capacitive Proximity Sensing as System of Choice for Driver Vehicle Interfaces** (Sebastian Frank, Arjan Kuijper) In HCI International 2020 – Late Breaking Papers: Digital Human Modeling and Ergonomics, Mobility and Intelligent Environments, Stephanidis C., Duffy V. G., Streitz N., Konomi S., Krömker H., (Eds.), Springer International Publishing (Cham, 2020), pp. 51–66, doi: 10.1007/978-3-030-59987-4_5

**2019** **Robust driver foot tracking and foot gesture recognition using capacitive proximity sensing** (Sebastian Frank, Arjan Kuijper) Journal of ambient intelligence and smart environments, pages 221-235, IOS Press, doi: 10.3233/AIS-190522.

**2018** **Enabling Driver Feet Gestures Using Capacitive Proximity Sensing** (Sebastian Frank, Arjan Kuijper) In proceedings of the 14th International Conference on Intelligent Environments (IE), Rome, IEEE, pp. 25-31, doi: 10.1109/IE.2018.00012.

**2017** **HUDConCap – Automotive Head-Up Display Controlled with Capacitive Proximity Sensing** (Sebastian Frank, Arjan Kuijper) In: Braun A., Wichert R., Maña A. (eds) Ambient Intelligence. AmI 2017. Lecture Notes in Computer Science, vol 10217, pages 197-213. Springer Springer International Publishing (Cham, 2017), doi: 10.1007/978-3-319-56997-0_16.

**2017** **AuthentiCap – A Touchless Vehicle Authentication and Personalization System** (Sebastian Frank, Arjan Kuijper) In Ambient Intelligence: 13th European Conference, AmI 2017, Malaga, Spain, April 26–28, 2017, Proceedings (2017), Springer International Publishing (Cham, 2017), pp. 46–63, doi: 10.1007/978-3-319-56997-0_4

**2016** **Method for determining the identity of a person in a seat of a vehicle** (Andreas Braun, Rainer Wichert, Sebastian Frank) Patent DE102014214978A1, Germany, Assignee: Fraunhofer Gesellschaft zur Förderung der Angewandten Forschung eV

**2015** **ExerSeat – Sensor-Supported Exercise System for Ergonomic Microbreaks** (Andreas Braun, Ingrid Schembri, Sebastian Frank) In: De Ruyter B., Kameas A., Chatzimisios P., Mavrommati I. (eds) Ambient Intelligence. AmI 2015. Lecture Notes in Computer Science, vol 9425. Springer International Publishing (Cham, 2015), pp. 236– 251, doi: 10.1007/978-3-319-26005-1_16.

**2015** **CapSeat: Capacitive Proximity Sensing for Automotive Activity Recognition** (Andreas Braun, Sebastian Frank, Martin Majewski, Xiaofeng Wang) In Proceedings of the 7th International Conference on

Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI '15, Association for Computing Machinery (New York, NY, USA, 2015), p. 225–232, doi: 10.1145/2799250.2799263

**2015** **The Capacitive Chair** (Andreas Braun, Sebastian Frank, Reiner Wichert) In: Streitz N., Markopoulos P. (eds) Distributed, Ambient, and Pervasive Interactions. DAPI 2015. Lecture Notes in Computer Science, vol 9189, pages 397-407. Springer International Publishing (Cham, 2015). doi: 10.1007/978-3-319-20804-6_36.

**2014** **Capacitive Proximity Sensing Supported Advanced Driver Assistance System** (Sebastian Frank, Xiaofeng Wang (supervisor), Andreas Braun (supervisor)) Master's Thesis. RheinMain University of Applied Sciences (Rüsselsheim, Germany)

**2012** **Simulation of Tractor Braking Cycles** (Sebastian Frank, Susanne Kuen-Schnäbele (supervisor), Michael Meid (supervisor), Mathias Klittich (supervisor)) Bachelor's Thesis. Kaiserslautern University of Applied Sciences (Kaiserslautern, Germany)

# B. Curriculum Vitae

## Personal Data

| | |
|---|---|
| Name | Sebastian Frank |
| Birth date & place | 17.04.1987 Landstuhl, Germany |
| Nationality | German |

## Education

| | |
|---|---|
| 2013 – 2014 | Master of Engineering in Vehicle Development and Production at RheinMain University of Applied Sciences, Rüsselsheim am Main, Germany |
| 2009 – 2012 | Bachelor of Engineering in Mechatronics at University of Applied Sciences Kaiserslautern, Germany |
| 2007 – 2008 | Study of Biophysics at Technische Universität Kaiserslautern, Germany |
| 2006 – 2007 | Study of Electrical Engineering at Baden-Württemberg Cooperative State University Mannheim, Germany |

## Work Experience

| | |
|---|---|
| 2014 – | Engineer, Opel Automobile GmbH, Rüsselsheim, Germany, Focus: Development automated HMI testing |
| 2013 – 2014 | Research Assistant, Fraunhofer Institute for Computer Graphics Research IGD, Darmstadt, Germany, Focus: HCI applications in smart environments |
| 2011 – 2012 | Research Assistant, Fraunhofer Institute for Industrial Mathematics ITWM, Kaiserslautern, Germany, Focus: Embedded Systems |

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