Passive Electric Field Sensing for Ubiquitous and Environmental Perception

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Passive Electric Field Sensing for Ubiquitous and Environmental Perception

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Abstract

Electric Field Sensing plays an important role in the research branches of Environmental Perception as well as in Ubiquitous Computing. Environmental Perception aims to collect data of the surroundings, while Ubiquitous Computing has the objective of making computing available at any time. This includes the integration of sensors to perceive environmental influences in an unobtrusive way.

Electric Field Sensing, also referenced as Capacitive Sensing, is an often used sensing modality in these research fields, for example, to detect the presence of persons or to locate touches and interactions on user interfaces. Electric Field Sensing has a number of advantages over other technologies, such as the fact that Capacitive Sensing does not require direct line-of-sight contact with the object being sensed and that the sensing system can be compact in design. These advantages facilitate high integrability and allow the collection of data as required in Environmental Perception, as well as the invisible incorporation into a user's environment, needed in Ubiquitous Computing.

However, disadvantages are often attributed to Capacitive Sensing principles, such as a low sensing range of only a few centimeters and the generation of electric fields, which wastes energy and has several more problems concerning the implementation. As shown in this thesis, this only affects a subset of this sensing technology, namely the subcategory of active capacitive measurements. Therefore, this thesis focuses on the mainly open area of Passive Electric Field Sensing in the context of Ubiquitous Computing and Environmental Perception, as active Capacitive Sensing is an open research field which already gains a lot of attention. The thesis is divided into three main research questions.

First, I address the question of whether and how Passive Electric Field Sensing can be made available in a cost-effective and simple manner. To this end, I present various techniques for reducing installation costs and simplifying the handling of these sensor systems.

After the question of low-cost applicability, I examine for which applications passive electric field sensor technology is suitable at all. Therefore I present several fields of application where Passive Electric Field Sensing data can be collected.

Taking into account the possible fields of application, this work is finally dedicated to the optimization of Passive Electric Field Sensing in these cases of application. For this purpose,

different, already known signal processing methods are investigated for their application for Passive Electric Field sensor data. Furthermore, besides these software optimizations, hardware optimizations for the improved use of the technology are presented.

Abstract

Electric Field Sensing spielt eine wichtige Rolle in den Forschungsbereichen Environmental Perception und Ubiquitous Computing. Environmental Perception zielt darauf ab, Daten aus der Umgebung zu sammeln, während Ubiquitous Computing das Ziel hat, Computer allgegenwärtig verfügbar zu machen. Dazu gehört auch die Integration von Sensoren, um Umwelteinflüsse auf unauffällige Weise aufzuzeichnen.

Electric Field Sensing, auch als Capacitive Sensing bezeichnet, ist eine häufig verwendete Sensormodalität in diesen Forschungsbereichen, beispielsweise um die Anwesenheit von Personen zu erkennen oder um Berührungen und Interaktionen auf interaktiven Oberflächen zu lokalisieren. Die elektrische Feldmessung hat eine Reihe von Vorteilen gegenüber anderen Technologien, wie z. B. die Tatsache, dass die kapazitive Messung keinen direkten Sichtkontakt mit dem zu messenden Objekt erfordert und dass das Messsystem kompakt aufgebaut werden kann. Diese Vorteile erleichtern eine hohe Integrierbarkeit und ermöglichen die Erfassung von Daten, wie sie für die Environmental Perception erforderlich sind, sowie die unsichtbare Einbringung in die Umgebung des Benutzers, wie sie für das Ubiquitous Computing benötigt wird.

Dem kapazitiven Sensorprinzip werden jedoch oft Nachteile zugeschrieben, wie z.B. eine geringe Reichweite von nur wenigen Zentimetern und die Erzeugung elektrischer Felder, was Energie verschwendet und weitere Probleme bei der Implementierung mit sich bringt. Wie in dieser Arbeit gezeigt wird, betrifft dies nur eine Teilmenge dieser Sensortechnologie, nämlich die Unterkategorie der aktiven kapazitiven Messung. Daher konzentriert sich diese Arbeit auf das noch offene Gebiet der passiven elektrischen Feldsensorik im Kontext des Ubiquitous Computing und der Environmental Perception, da die aktive kapazitive Sensorik ein offenes Forschungsfeld ist, dem bereits viel Aufmerksamkeit geschenkt wird. Die Arbeit gliedert sich hierfür in drei Hauptforschungsfragen.

Zunächst beschäftige ich mich mit der Frage, ob und wie Passive Electric Field Sensing auf kostengünstige und einfache Weise verfügbar gemacht werden kann. Dazu stelle ich verschiedene Techniken zur Reduzierung der Installationskosten und zur Vereinfachung der Handhabung dieser Sensorsysteme vor.

Nach der Frage der kostengünstigen Anwendbarkeit untersuche ich, für welche Anwendungen die passive elektrische Feldsensorik überhaupt geeignet ist. Dazu stelle ich

verschiedene Anwendungsfelder vor, in denen Daten mit Passive Electric Field Sensing erhoben werden können.

Unter Berücksichtigung der möglichen Einsatzgebiete widmet sich diese Arbeit schließlich der Optimierung von Passive Electric Field Sensing in diesen Anwendungsfällen. Zu diesem Zweck werden verschiedene, bereits bekannte Signalverarbeitungsmethoden auf ihre Anwendbarkeit für Passive Electric Field Sensing Daten untersucht. Darüber hinaus werden neben diesen Software-Optimierungen auch Hardware-Optimierungen für den verbesserten Einsatz der Technologie vorgestellt.

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1. Introduction

1.1. Ubiquitous and Environmental Perception

Ubiquitous Computing has been an important research topic for nearly 30 years. As stated by Mark Weiser, "Ubiquitous computing has as its goal the non-intrusive availability of computers throughout the physical environment, virtually, if not effectively, invisible to the user" [88]. Ubiquitous Perception has a similar goal relevant to sensing and measuring environmental extents. The objective of Ubiquitous Perception is to aggregate environmental data while keeping the sensing peripherals virtually or really invisible. Virtual invisibility describes the ability to not affect certain conditions in a measurement scenario, while real invisibility means the complete disguise of sensing equipment.

Nowadays the concealment of sensors is a necessity in many areas of applications. For surveillance purposes, while it may be beneficial to install cameras and other surveillance hardware visible on purpose for others to deter intruders from potential attacks, they may be easily destroyed or damaged in their function of surveillance equipment. For this reason, cameras or microphones may be hidden to hamper the destruction of them.

In research, while conducting experiments and studies that involve human participants, the Hawthorne effect describes that persons may alter their behaviour if they are knowingly observed. Although the Hawthorne effect is discussed controversially [1][38], one can argue that a person can deliberately choose to alter their behaviour when they are conscious of their own observation, while this is not possible if a person does not know and does not suspect that they are under surveillance.

For non-human centered research, the motivation to hide sensing equipment are equivalent; Animals may be scared or curious of sensing hardware and thus alter their behaviour when noticing them. Therefore photographers are hiding themselves and their equipment. Even in scenarios, where the sensing equipment is allowed to be visible, a higher level of integration is most likely to be an advantage. In ornithology for example, a researcher may choose to equip birds with a tracking device to analyse their path of flight. While the need for invisible equipment is secondary in this use-case, it is primarily desirable to chose small and lightweight sensors to not influence the capability of the birds to fly long distances. In this case, the tracking device is virtual invisible.

For these previously mentioned and many more reasons, Ubiquitous Perception is a key methodology in a large variety of application areas and ongoing research.

Environmental Perception on the other hand does not make a statement about the visibility or integration of a technology, but rather describes the ability of a device to perceive its surroundings. The term Environmental Perception is also used in psychology for the perception of certain environmental influences.

It goes without saying that this capability is crucial for a lot of applications. Therefore, Environmental Perception is a hot research topic in various fields.

In general, navigation tasks require a robust perception of the environment. This includes navigation in robotics [16] or navigating through traffic. In the field of autonomous driving, environment perception is a research discipline which gained a lot of attention these years. It can be achieved by using sensors like cameras, LiDAR and Radar and is crucial to enable vehicles to understand their surroundings [94].

Although these technologies are excellent for Environmental Perception because they can have high resolutions, sampling rates, and measurement ranges when implemented appropriately, these techniques are problematic from a privacy perspective. Cameras and other imaging techniques record a large amount of excess information that is not needed for many problems. For example, when people's gestures and postures are to be recorded, their faces are also recorded. This information can be used to directly determine the identity of the user, even if the actual purpose of the application only involved pose recognition. Critical private information such as the user's identity must then be removed manually afterwards in such use cases. However, even in applications where the subsequent removal of this information is not omitted for time or cost reasons, the user must always rely on the manufacturer of such systems that the deletion of this data is done with sufficient quality.

For this reason, it is desirable to capture only as much information as is really needed for the corresponding application. By using appropriate sensor technology, which minimizes the amount of excess information, this can be achieved cost-effectively and efficiently.

1.2. Research Questions

The focus of this thesis is the categorisation, examination and optimization of Passive Electric Field Sensing technology. One of the ways this is achieved in this thesis is through the implementation of various prototype applications of Passive Electric Field Sensing. The statements on the usability of the technology are supported by user studies. In addition, this thesis strives to give a complete overview of current state-of-the-art research while still treating physical basics and comparisons to related technologies. Overall, this thesis wants to capture every important aspect of Passive Electric Field Sensing and how to apply it for ubiquitous and environmental perception.

Therefore, this thesis is structured around several research questions that on one hand reflect the scientific contribution of this thesis while on the other hand can be used to guide the reader throughout the document.

The core topic of this thesis is Passive Electric Field Sensing. The beginning of this thesis will first look into the historical origins of the terminology Electric Potential Sensing. In addition to the historical development of the term, it will be clarified why this terminology was further specified. Since the reasons for this term specification are mostly justified on a physical basis, the basic mathematical models of this family of technology will be explained alongside. All these characterizations of Passive Electric Field Sensing will be answered at the beginning of this thesis to form a foundation for the following research contributions.

A sole definition of the term Passive Electric Field Sensing and its roots is insufficient to discriminate this technology from physically similar technologies. Hence, this thesis will additionally cover the basics of related capacitive technologies to further differentiate between them and Passive Electric Field Sensing. This especially will cover the so-called different modes of capacitive sensing (Loading Mode, Shunt Mode, Transmit Mode) with their physics and how to distinguish them from Passive Electric Field Sensing. Overall, the survey of these classical modes in the field of capactive sensing combined with the emergence of the term Passive Electric Field Sensing will represent the basis for the upcoming discussion of research questions.

After defining the terminology, the subsequent first research question is more practical in nature. It concerns the implementation of this technology. How can a Passive Electric Field Sensor be structured? What forms of implementation are possible? What advantages and disadvantages arise out of the different implementations? These questions all have a common goal in mind, which will be clarified with the following Research Question 1:

Research Question 1 (RQ1) Can Passive Electric Field data be collected in a manner that improves usability and deployment cost?

To answer Research Question 1, this thesis will contribute a discussion of different sensor implementations with different degrees of complexity, as well as effectiveness regarding their measurement range and quality. In addition, it will be elaborated how to collect Passive Electric Field data while maintaining or improving the usability for sensors using this technology through simultaneously decreasing deployment efforts. Usability in the context of this work refers to the use of Passive Electric Field Measurement in the research environment and for general prototyping. To achieve this, techniques to eliminate the ground reference for these kind of sensors as well as a toolkit for collecting Passive Electric Field data will be introduced.

But the effectiveness of a sensor not only depends on its implementation alone. Different use-cases may benefit from different implementations. That is why another important part of this work will be the presentation of a wide variety of use-cases for Passive Electric Field Sensing. This directly leads to Research Question 2:

Research Question 2 (RQ2) For which areas of application is Passive Electric Field Sensing feasible?

Of course, it is impossible to cover all possible use-cases, just because there may be still novel use-cases for Passive Electric Field Sensing that simply have not been found yet. So the compilation of use-cases for this technology and hence the contribution of this thesis for this research question will be a collection of the current state-of-the-art publications. Afterwards, the feasibility of the technology will be further discussed. All of this will be done by contributing example implementations of selected application areas for the sensors. As already mentioned, the effectiveness of a sensor will vary depending on the use-case it is used for. This brings us to the last research question that has to be answered in order to provide a well reflected overview over Passive Electric Field Sensing.

Research Question 3 (RQ3) How can the use of Passive Electric Field Sensing be optimized?

With this last Research Question 3, this thesis will issue several use-case depend optimizations and optimizations that can be applied even if the exact use-case is not known. Optimizations comprise the adjustment of algorithms, signal filtering (implemented in hardware and in software) and the appropriate use of electrodes and shielding.

1.3. Structure of this Work

This section provides a concise overview of this work.

Chapter 2 lays the basis for the understanding of the physical background for the following chapters. The chapter first gives an introduction to the origins of Passive Electric Field Sensing and discusses the naming of it in respect to the physical properties of this technology. Further on, differences and parallels of con-generic technologies are presented to complete the physical overview.

After the explanation of the physical basis, Chapter 3 presents several approaches to improve the deployment of Passive Electric Field sensors in regard to their cost and their usability. That also means that this chapter will answer Research Question 1. The chapter is based on the publications [B.1.1], [B.1.4], [B.1.13] and [B.2.3], which also represent the foundation of the patent found in Appendix [D]. To begin with it will be shown how the measurement technology of these sensors can be improved to enhance the detection range and thus facilitate the deployment by increasing the potential areas where a sensor can be deployed in the first place. Afterwards, a toolkit using this optimized measurement technique will be presented to demonstrate that the usability of Passive Electric Field sensors does not has to suffer while optimizing deployment cost. In the last part of the chapter, it will be investigated how the deployment cost can be reduced even further by examining the total number of sensors needed to classify certain human activities. The results show that even setups with less sensors are able to perform equally in comparison to sensor setups comprised of a bigger number of devices, completing the contributions of this chapter.

Following the optimization of the deployment of Passive Electric Field Sensors, several sensor systems are deployed in Chapter 4 to investigate potential application areas for this technology and ultimately answer Research Question 2, based on publications [B.1.2], [B.1.7], and [B.2.1]. The selected areas of applications are chosen in such a way that all stages of the daily routine of a potential user is covered. While applying Passive Electric Field Sensing to different domains of daily life activities, pro and cons of its use will be worked out. This contributes to understand in which areas of application this technology is feasible and will hence answer RQ2.

With the previously gained knowledge about the limitations of Passive Electric Field Sensing, based on Publication [B.2.4], Chapter 5 will discuss in the last part of this thesis how to optimize the hardware setup to counteract the recently learned limitations. Additionally, not only the hardware setup will be optimized, but also the signal processing of the acquired data. This will take place by considering the technological limitations and how commonly known signal processing techniques can be adopted to be used with Passive Electric Field Sensing. Thereby, Chapter 5 will answer Research Question 3.

2. Categorization of Electric Field Sensing Technologies

This chapter distinguishes the terms Electric Field Sensing, Active Electric Field Sensing and Passive Electric Field Sensing plus their variations such as Electric Potential Sensing. At the same time, the usage of these terms throughout this thesis is defined more precisely. Since many aspects of the underlying technologies are related, a more in-depth inspection of the underlying physical principles is conducted.

This chapter is a summary to set the groundwork for the physical basis of Passive Electric Field Sensing and at the same time create a rundown on the historical usage of this term. That implies that this chapter gathers already existing information about Passive Electric Field Sensing and hence does not introduce new concepts for this technology.

Hence, the focus of this chapter is to clarify the term Passive Electric Field Sensing and separate it from the very similar term Electric Field Sensing. In addition, the expression Electric Potential Sensing is used in a similar way to Passive Electric Field Sensing and by having a deeper look into the fundamental physical basis it is made clear why Passive Electric Field Sensing is used consistently in this work.

Later on, the principle of operation is reported. This section comprises not only Passive Electric Field Sensing, but the most common related technologies as well that are entitled as Electric Field Sensing. This enables the reader to directly compare these technologies and gives an overview of existing capacitive systems.

All these facets summed up enables the reader to understand what Passive Electric Field Sensing is and how this technology emerged.

2.1. Term Definition and Distinction

Electric Potential Sensing, Historically, the first term to describe the underlying technology, which in the context of this scope of this paper as Passive Electric Field Sensing, was coined by Clippingdale et *al.* in 1994 [10]. In this article, Clippingdale et *al.* described a new prototype for ECG measurements, using a system comprised of 25 ultrahigh impedance electric potential sensors that did not require any direct contact with the body to perform the measurement. Clippingdale et *al.* illustrate the electric potential sensor as seen in Figure 2.1. As depicted in their publication, this kind of sensor does not require an ohmic connection to the test person. Instead, it is sufficient to have the input electrode coupled purely in a capacitive way. This means that the signal which the sensor measures can be expressed as a function of the electric field contained in the capacitor that is created between input electrode and user.

Prance et *al.* then further refined this technology in their paper An ultra-low-noise electrical-potential probe for human-body scanning [59], which already follows their own naming scheme for this technology, namely Electric Potential Sensing. The publication describes how Prance et *al.* lower the noise level of the electric potential probes under 2 µVHz$^{-1/2}$. This particular design is based on an INA 116 - a dual input instrumentation amplifier with an input impedance of around $10^{15}\Omega$. As in the preceding design, the author claims that the probe can be arranged to have an input that purely relies on a capacitive measurement principle.

This shows that the presented technology is closely related to electric field sensing, which is why it should be entitled as such. A main difference between "classical" electric field sensing and the technology used in the sensors described by Clippingdale et *al.* and Prance et *al.* is the fact that the measured electric field is not artificially created, as for example by a capacitive Loading Mode sensor. So by denoting this kind of technology with Electric Field Sensing, which is technically correct, leads to misunderstandings of the underlying technology because of the momentary use of the term Electric Field Sensing in literature, which is examined later on in this chapter.

Because of this, in this work, the expression Passive is added to the term Electric Field Sensing to stress the property of this technology to measure displacement currents generated by natural fields. This terminology is also enforced by other authors, like Noras et *al.* [53] and Xinyao et *al.*. In their article "Indoor Occupancy Awareness and Localization Using Passive Electric Field Sensing", in which the authors presents a system that estimates the number of persons occupying a room based on Passive Electric Field Sensing [73]. As proposed in this chapter, they use the term Passive to demarcate this technology from capacitive sensing technologies.

Likewise to the expression Passive Electric Field Sensing, Active Electric Field Sensing is used for technologies that create fields by using oscillators and similar methods that generate alternating currents. Figure 2.2 depicts this discussed categorization of Passive Electric Field Sensing, as well as the categorization of active capacitive technologies.

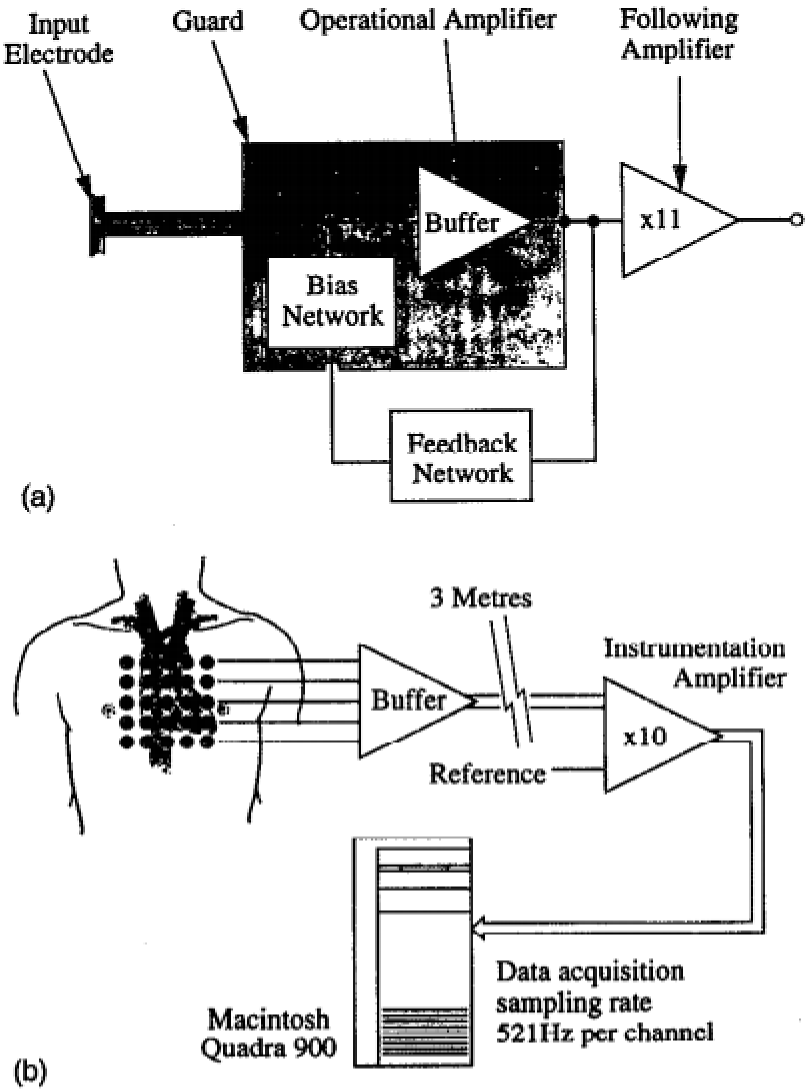


Figure 2.1.: Electric potential sensor as described by Clippingdale et *al.* [10]

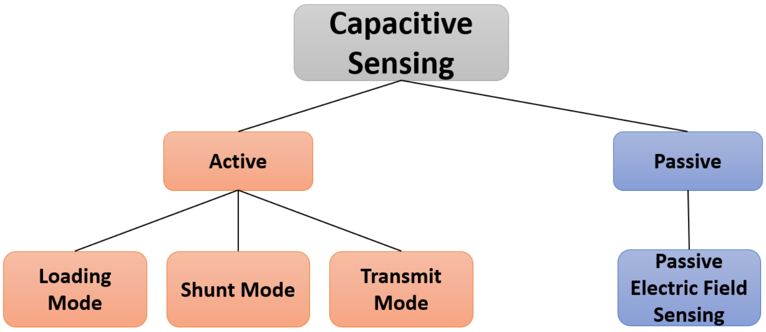


Figure 2.2.: Categorization of Passive Electric Field Sensing in the domain of capacitive sensing

2.2. Active Electric Field Sensing

The term Active Electric Field Sensing is used because of the electric field which is actively created by this type of technology. This electric field is a result of the measurement principle. To actively generate an electromagnetic field, an alternating current is needed. Active Electric Field Sensing, or capacitive sensing, charges and discharges an electrode, thus creating an electromagnetic field. The most common use-case for this technology is the approximation of the distance between an electrode and a conductive object (which naturally includes living beings). Other use-cases include position sensors [50], rotary encoders [92], occupancy detection [64], the detection of several molecules like adrenalin and glucose [14][9] and countless more use-cases [90][3][76][8][74].

This is realised by measuring the time needed for a single charge/discharge-cycle or by measuring the amplitude of a received charge/discharge-signal from a sender electrode. The total amount of energy that can be stored in between the electromagnetic field of the electrode and a conductive object to which the distance shall be approximated is a function depending on the distance of these objects. If these conductive entities approach each other, more energy can be stored in this virtual capacitor created by electrode and object, hence the time needed for a charge/discharge-cycle is longer. This measurement principle relies on the capacitive coupling effect. The electrical capacity C between two conductive objects, separated by a dielectric material with a relative permittivity ϵ_r, with a surface area A and the distance d is:

$$C = \epsilon_0 \epsilon_r \frac{A}{d} \tag{2.1}$$

where ϵ_0 is the vacuum permittivity. Since the capacity C can be expressed as a function of voltage U and charge Q as follows:

$$C = \frac{Q}{U}. \tag{2.2}$$

We can relate the time t to the distance d of the two objects. This is because the current I is

$$I = \frac{\partial Q}{\partial t} \tag{2.3}$$

In combination, these equations result in

$$I\partial t = \partial(U\epsilon_0\epsilon_r\frac{A}{d}). \tag{2.4}$$

In other words, the distance d of two conductive objects with the surface A is proportional to the time needed to charge them with the constant current I to a voltage difference of U volts. This fact can be exploited to measure the capacitance of any given capacitor. One can simply measure the time needed to charge the capacitor with a predefined current.

A more practical problem of this approach poses the charging behaviour of a capacitor. The time needed to charge an ideal capacitor is given by Equation (2.5).

$$t = \tau \ln(\frac{q}{Q - q}) \tag{2.5}$$

where t is the time needed to charge the capacitor that can hold a maximum charge of Q. The variable q constitutes the targeted charge of the capacitor, which naturally cannot be larger than Q. Hence $q \leq Q$. The constant τ is dependent on the overall circuit. It is derived by

$$\tau = RC \tag{2.6}$$

with the capacitance C of the capacitor and the resistance R which is connected in series with the capacitor and defines the overall amount of the charging current. The implied problem is that for any capacitor, the time needed to fully charge it to its maximum capacity Q, the time needed is:

$$\lim_{q \to Q} t \to \infty. \tag{2.7}$$

For this reason, one cannot construct a circuit that measures the capacitance of a capacitor by fully charging it. A solution to this problem is to never fully charge the capacitor, but instead charge it to an arbitrary, predefined voltage level smaller than the supply voltage. However, measuring the duration of a single charge cycle (or discharge cycle) would be afflicted by too much noise or would result in a high cost of the implementation because of the need for very precise clocks.

There are several ways around this problem. By increasing the maximum charge the capacitor can hold, the charging time increases. A drawback of this solution is that Q can only be increased by increasing the charging voltage (see Equation (2.2)) since C is the variable to be measured. Therefore, to significantly increase the maximum charge, the electrode would have to be charged to dangerously high voltage levels, making this solution infeasible for most applications. This is the reason why the electrode is commonly only charged up to several volts, for safety reasons and because the design of low voltage circuitry does not require any kind of step-up voltage boosters, simplifying the design process of such a circuit. Charging the electrode to higher voltages would require more time, making a time measurement more easy and precise, but impractical in reality. To resolve the problem with minimal cost and safety issues, not a single charge/discharge cycle is measured, but several at once.

There are of course other measurement principles that avoid this problem completely by using different measurement techniques. A good example for this is the work of Iqbal et *al.* [36]. In their work, the authors describe a capacitive sensor based on phase modulation with a range up to 150cm. The sensor uses a single sine-wave generator at a 10kHz frequency, which is fed into the measurement electrode with a size of 16cm^2 over a potentiometer. The same sine wave is simultaneously fed into a comparator stage, which compares the filtered output of the electrode to the original sine wave. According to Iqbal et *al.*, the phase shift ϕ between both sine waves is calculated as:

$$\phi = -\arctan(2\pi f RC) \tag{2.8}$$

Aforementioned, the potentiometer through which the sine wave is fed to the electrode forms an RC filter in conjunction with the electrode, which directly influences the phase shift of the compared waves. Note that f is constant (10kHz) in this equation as well as the potentiometer value R, which is calibrated beforehand. The capacity C is the value of the capacitor formed by the electrode and the approaching person and thus varies according to the distance of the person to the electrode.

2.2.1. Loading Mode

To implement a classical capacitive measurement based on the Loading Mode principle, an oscillator to generate a square wave is needed. The oscillators has to satisfy the following conditions:

1. The output of the oscillator has to be a constant current source. This is because of Equation (2.3): The overall charge on the electrode is dependent on the the charge time and the charge current. To have a constant current source means that one is able to determine the charge Q, and with the combination of the voltage and Equation (2.2) finally the capacitance of the virtual capacitor formed by any electrode.

2. The oscillators input has to be dependent on its own output voltage. A simple timed oscillator is not sufficient to implement a capacitive Loading Mode sensor because if the oscillator would switch between a charge- and a discharge cycle only based on time, the charge/discharge time would always be the same, hence defeating the purpose of measuring different charge times for differently sized capacitors. That is why the oscillator has to switch between high and low voltage level when its output is reaching a predefined level of voltage.

The resulting voltage of an electrode that forms a virtual capacitor with another object, charged and discharged by an oscillator with a square wave is shown in 2.3. As already mentioned, since it is impossible to fully charge the capacitor, Figure 2.3 is based on a simulation that assumes a supply voltage of 3.3 volts and standard CMOS voltage levels for the switching points between charge- and discharge cycles.

Figure 2.3 illustrates several charge- and discharge cycles of an electrode. As already mentioned, to conduct a measurement with such an oscillator as shown in 2.3, a count of all occurring charge- and discharge cycles in a fixed amount of time has to be performed. Figure 2.4 shows an example of a measurement performed in such a way. A different approach, as shown by Große-Puppendahl et *al.* [24], is to count a set amount of edges of the oscillating circuit while measuring the time needed to reach this constant amount. Both approaches have different advantages and disadvantages.

Counting a set amount of pulses and measuring the time requires the use of a precise clock, which makes this measurement technique potentially more expensive. On the other hand this allows for more exact values in comparison to the pulse counting method because counting fractions of a charge- and discharge cycle is not possible, while reducing the smallest unit for the time reference can be done by choosing a better clock. The number of charge- and discharge cycles of a capacitive sensor can be up to several million cycles per second and to measure fractions of such short cycles, the clock has to be several times faster (depending on the desired sensor accuracy).

On the other hand, using a fixed amount of time and counting the occurring pulses also requires precise clocks. But since the amount of time used for a measurement can be chosen

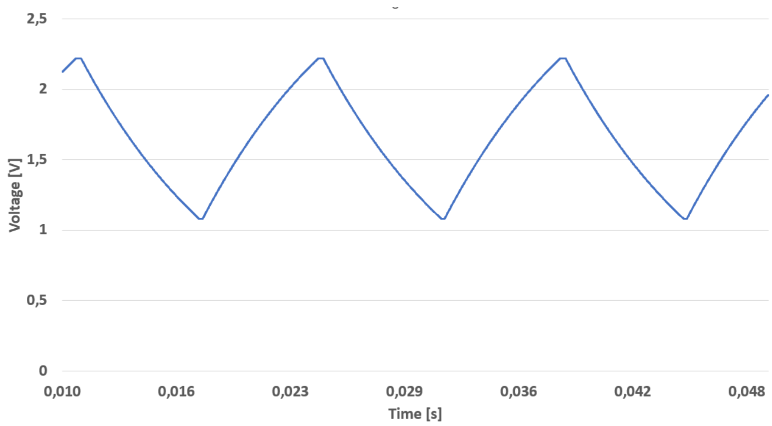


Figure 2.3.: Simulation of several charge- and discharge cycles with typical CMOS logic levels, which can be derived as a concatenation of several exponential functions

freely, the clock speed as well as the clock accuracy can be neglected. Important is the repeatability or precision of the used clock. This makes the design very cost efficient; Low frequency crystals for clock generation (for example 32768Hz) with frequency tolerances as low as 10 ppm and less are price wise in the range of cents.

One of the most commonly used building blocks to build a capacitive Loading Mode sensor is the 555 Timer IC. The 555 Timer IC is one of the oldest ICs that is still in production [6], for over 48 years to this point. That makes this IC equally cheap than the previously mentioned low frequency crystals. This design was also used by S. Frank. In his thesis [15], S. Frank described the use of capacitive sensing regarding the operation in automotive applications. He first defined three research questions that are used as a guideline throughout the thesis. These questions involve the usage, the enhancement as well as privacy concerns of capacitive proximity sensors. He then defines a development process that can be applied to several developments that focus on capacitive proximity sensing in vehicles. This process is the basis for all further chapters and the implementations covered by those. Overall, the development of five different applications is covered by the thesis. He mainly uses capacitive sensors in the Loading Mode configuration for his applications. The applications include both interactive and non-interactive examples. This demonstrates the flexibility of the rather oldfashioned capacitive Loading Mode sensor design based on the 555 Timer IC.

One of the most critical components besides the clock generator is the source of a constant current. This is simply the result of Equation (2.4). The time needed to charge a

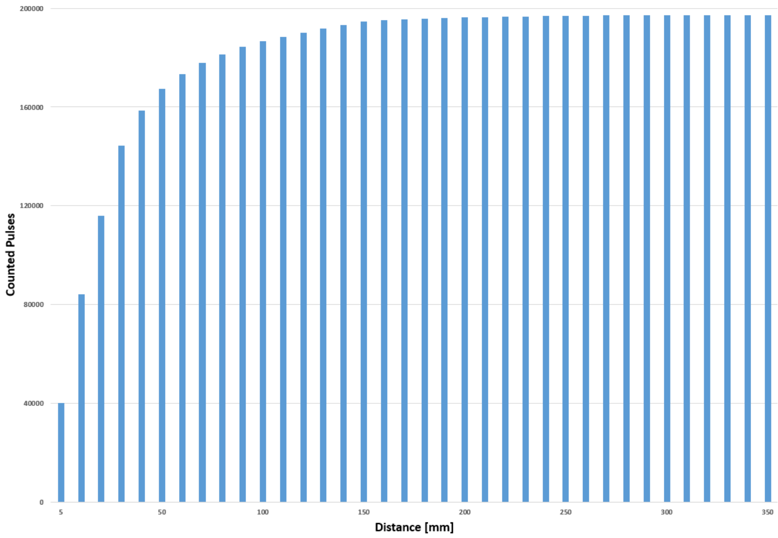


Figure 2.4.: Sample measurement of a copper plate while varying the distance to the sensing electrode

capacitor is only proportional to its size as long as the current used for charging is constant. It is not possible to apply this measurement principle if the current is an unknown and rapidly changing variable.

The data visualized in Figure 2.5 and Figure 2.6 emphasizes this statement. Figure 2.5 is an illustration of capacitive Loading Mode data recorded over a period of one hour in a shielded environment. Figure 2.6 shows the same sensor, again recorded for an hour in a completely shielded environment, but with the difference of activating the Bluetooth module of the micro-controller in charge of counting the pulses generated by the Loading Mode circuit. The Bluetooth peripheral of the micro-controller increases the energy consumption for short periods of time so that the decoupling capacities of the sensor cannot completely cover the energy demand for radio operation. For the normal operation of the micro-controller, this drop in supply voltage does not pose a problem, since it is hardly noticeable. The recorded data indicates that the voltage drop is around 50mV, which is tolerated by nearly every micro-controller. But even this small drop in supply voltage means a five times bigger noise margin of the Loading Mode sensor, as depicted by Figure 2.5 (the noise spans approximately over 10 pulses) and Figure 2.6, where the noise divergence of the individual samples is about 50 pulses. Since the number of pulses in a capacitive measurement correspond to the distance of the object to be measured, a higher noise level leads to a lower resolution. The ideal capacitive sensor

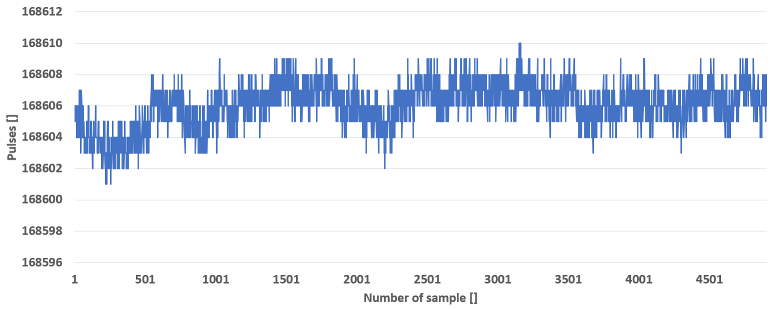


Figure 2.5.: One hour capacitive measurment without any activated radio. Noise divergence: approx. 10 pulses

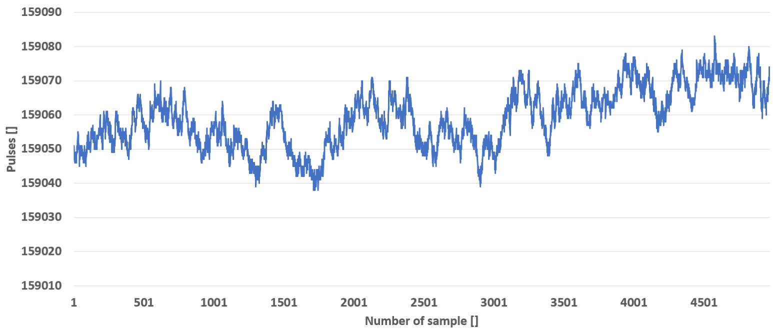


Figure 2.6.: One hour capacitive measurment with activated Bluetooth peripheral group. Noise divergence: approx. 50 pulses

would generate a flat line.

To verify that this additional noise in the measurement does not originate from the 2.4GHz signals that couple into the electrode, the development board containing the capacitive Loading Mode sensor was programmed with different firmware versions which used different peripherals. After that, the maximum detection in which it is possible to distinguish an approaching object from the noise of the sensor was measured for each firmware. Then, a super capacitor was attached to the capacitive Loading Mode sensor while using the firmware version with the lowest detection range. The super capacitor has a capacity of 15F. Figure 2.7 depicts the sensor with the attached super capacitor. Note that the advantage of this huge capacity comes with the price of a slightly lower discharge rate than a normal tantalum or ceramic capacitor.

The results are presented in Figure 2.8. For the exact metric used in this figure, see

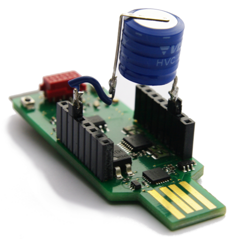


Figure 2.7.: Development board capable of Loading Mode measurements with attached super capacitor

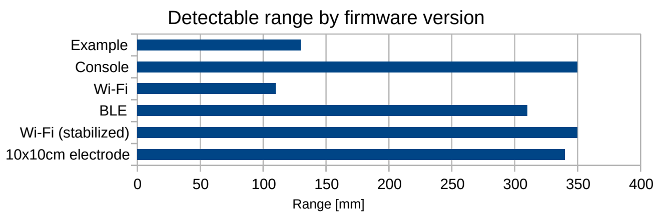


Figure 2.8.: Detection range for different firmware versions by name

Section 3.2.10. For the sake of completeness, a condensed description of the depicted firmware versions is given:

- "Example": This firmware is a not optimized implementation, based on examples provided by the micro controller documentation. It uses software tasks to query the pulse counter unit of the micro controller. While this works to a certain extend, the processor can delay tasks if more important, critical code has to be handled like interrupts or if other tasks with same or higher priority are queued up. The delayed time to read the pulse counter register leads to a higher values in it, leading to a wrong measurement result. That is why the performance of this firmware compared to others is underwhelming despite the fact that nearly no other peripherals of the micro controller were activated.
- "Console": An implementation that fixes the performance issues based on context switching and inconsistent measurement results because of varying processor load. This was done by executing time critical code directly in a given timer interrupt handler instead of using task switching. This version is named "Console" because it

also implemented a console using the UART peripheral of the micro controller that can be used if the sensor is directly connected to a PC.

- "WiFi": An alteration of the Console firmware version with activated WiFi radio.
- "BLE": In this firmware version, Bluetooth Low Energy was used instead of WiFi. Note that the peripheral for both, WiFi and BLE, is the same 2.4GHz radio. The difference is mainly the protocol used. Shorter packet frames and less overall traffic is the focus of Bluetooth Low Energy compared to WiFi.
- "WiFi (stabilized)": The same Firmware version as WiFi, but using a 15F super capacitor as a bypass capacitor to provide high currents for short amount of times.
- "10x10cm electrode": The last entry in the comparison diagram is a 10cm x 10cm electrode and a sensor array setup in which the second sensor actively used WiFi. This sensor was placed outside the shielded environment to isolate the effect of power drainage. This was done to demonstrate that not only the stability of current supply plays an important role for the overall detection range of a sensor, but also the size of the used electrode.

As the results show, the firmware version that activates the 2.4GHz radio in combination with IEEE 802.11 based protocol has the most noisy measurement and hence the lowest detection rate. For a more detailed explanation of the used metric, see Section 3.2.10. This firmware version was then combined with a super capacitor which improved the measurement range to the baseline firmware version without any activated peripherals.

2.2.2. Shunt Mode

In shunt mode, an electric field is created between a transmitter and a receiver electrode. This is done by modulating an alternating current on the transmitter electrode. Because of this, shunt mode is, just as the capacitive Loading Mode sensors, an active capacitive technology.

A main difference between Loading Mode and shunt mode is the absence of the second electrode in Loading Mode. Capacitive Loading Mode measurements use, as explained in the previous subsection, the same electrode as transmitter and receiver simultaneously.

Capacitive shunt mode measurements on the other hand use one electrode to send out an electric field to a second receiver electrode. A lumped system model of such a sensor is shown in Figure 2.9.

The object to be measured is depicted as a human hand in Figure 2.9. When the object to be measured approaches both electrodes, C_{rt} will decrease while C_{hr} and C_{ht} increase

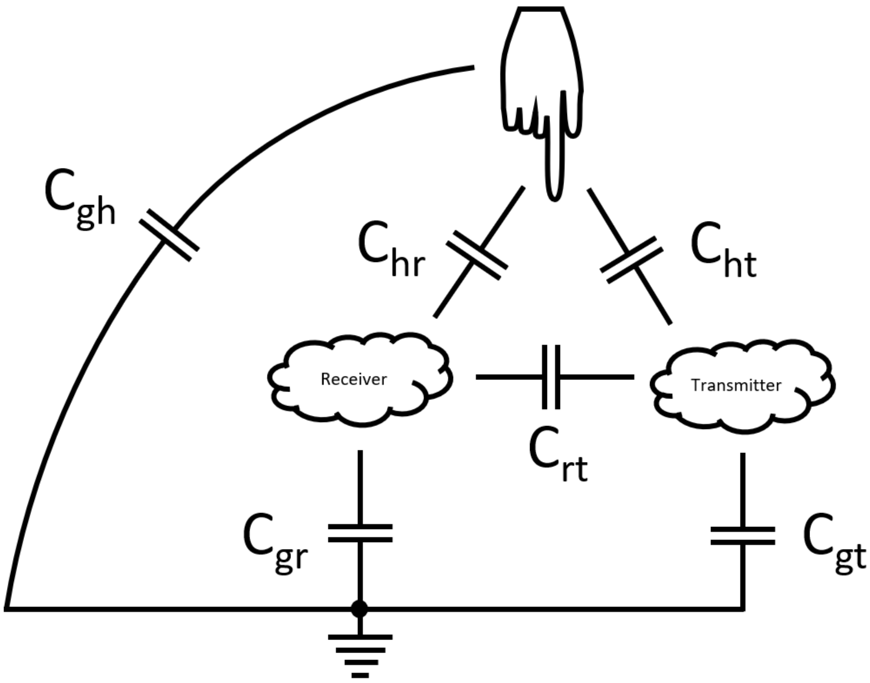


Figure 2.9.: Lumped component model of a shunt mode system

in capacity [71]. Decreasing the capacitance between receiver and transmitter electrode leads to a smaller displacement current between them, because the current is conducted over the object to be measured to ground over C_{gh}. This drop in current is measured by the receiver. The smaller the displacement current, the closer the object to be measured.

An advantage of shunt mode over Loading Mode measurements is the ability to create sensitive areas with a large amount of measurement points. This was, among others, shown by Zhang et *al.* in their publication [91]. Zhang et *al.* constructed a wall with a conductive diamond pattern painted underneath, which they used as sender- and receiver electrodes. As a result, the entire wall was turned into a capacitive shunt mode sensor. As shown, every crossing of a sender electrode and receiver electrode creates a measurement point. Thus, four receiver electrodes and five sender electrodes for example are capable of distinguishing between twenty different measurement positions. A Loading Mode setup with the same number of electrodes would only be able to distinguish between nine different positions.

2.2.3. Transmit Mode

Transmit mode is similar to capacitive shunt mode measurements. The lumped circuit model remains the same as shown in Figure 2.9 for the shunt mode measurement. In transmit mode, C_{ht} is substantially bigger than C_{hr} [71]. This means that the measured object itself becomes the transmit electrode.

As already explained previously in the shunt mode section, the result of the measurement is the measured displacement current picked up from the receiver electrode.

2.3. Passive Electric Field Sensing

In classical literature, the term Electric Field Sensing (without the addition of an adjective like active or passive) is used for capacitive sensing - Loading Mode, Shunt Mode or Transmit Mode [70][69][95][93].

Passive Electrical Field Sensing relies on the capacitive coupling effect, too. This classifies the technology as a form of capacitive technology. But in contrast to classical capacitive sensing, or Active Electric Field Sensing, Passive Electric Field Sensing does not create an electromagnetic field itself. The technology uses the external, natural creation of electric fields.

A charged object, that is moving near a conductive object, will induce a small current, since both objects are coupled by the electrical field. Both objects form a capacitor. Instead of measuring the time of a charging process, Passive Electric Field sensors measure the voltage. The basic relation between voltage (U), charge (Q) and capacity (C) is now used in the form:

$$U = \frac{Q}{C}$$

Due to the triboelectric effect and other sources of static electricity, nearly every object carries a charge. If a charged object moves near the electrode, it causes the charge in the electrode to move accordingly, resulting in a current that can be measured. The drawback of this measurement principle is, as already stated above, that the charge has to move. Note that this does not necessarily mean that the object itself has to move. A static object cannot be detected this way. Because of Ohm's law and because the induced current is very small, the resistance on the electrode has to be high to measure the change in voltage. To achieve a high resistance in a giga-ohm range, an operation amplifier is used in a unity gain buffer configuration, as shown in Figure 2.10.

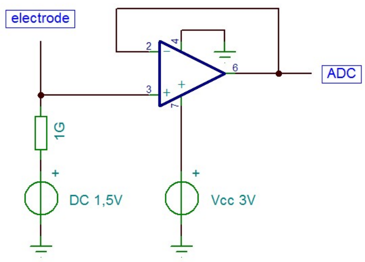


Figure 2.10.: The basic measurement circuit of our electric field sensor implementation.

An advantage over classical capacitive sensing is the increased range. Passive Electric Field Sensing can be used to measure objects several meters away from the sensing electrode, as shown for example by Rekimoto et *al.* [51]. Active capacitive sensing is well suited in close range proximity sensing [24]. Another advantage over capacitive sensing is the reduced energy consumption since no electrical field is formed. The measurement itself as shown in Figure 2.10 only consumes several nano-amps. A similar efficient system is shown by Cohn et *al.* [12]. The operation amplifier used in our electric field sensor implementation, the MCP604x from Texas Instruments, only uses 600nA as quiescent current. All other components drain even less power so that the sensor consumes overall less than 800nA.

A disadvantage with the purely Passive Electric Field Sensing is that only moving objects can be detected since a current has to be induced in the electrode, which is only possible by moving electrical charge. This can be done mainly in two different ways:

1. A charged object moves by, similar to a charged balloon moving close to some hair, moving it in the process.
2. A constantly changing electrical field is emitted, as, for example, every cable in households does which transmits an alternating current.

Classical capacitive sensing, on the other hand, can measure the distance of objects despite the fact that they are moving or not. The sole presence of a conducting object changes the capacitance and hence can be detected.

Passive Electric Field Sensing also cannot measure the distance to the approaching object. That is because the measured voltage is a function of charge and capacitance. The electrical charge of the same object can vary over time and even change its sign. Trivial everyday activities, such as walking over a carpet or washing hands are affecting the amount of charge carried by a person. For this reason, the amplitude and the sign of such a voltage measurement give only limited information.

2.4. Summary

This chapter summarized the origin of the term Passive Electric Field Sensing as found in current scientific literature. As shown, it originated in a field closer to clinical applications [10][59], rather than user interaction or Ubiquitous Computing as used by Weiser et *al.* [87].

It was justified why, throughout this work, we stick to the term Passive Electric Field Sensing to clearly state the underlying function principle of the used technology and to demarcate it from more classical capacitive technologies, like capacitive Loading Mode for example.

In addition, the physical distinctions were shown compared to similar technologies such as capacitive measurements using Loading Mode. These technologies often have similar names and identifiers in literature because they involve the creation of electric fields or measuring some characteristics of electric fields. Hence they all belong to the family of electric field sensing technologies.

Therefore, in this first section of this thesis, the question on what Passive Electric Field Sensing is was answered in a historical, as well as in a physical way. Both issues combined give the reader an understanding of what Passive Electric Field Sensing really is, why this term is used further on and what the underlying principles of this technology are; Passive Electric Field Sensing is closely related to electric field sensing technologies since they all rely on capacitive coupling effects. Yet, because of its passive nature, this technology cannot be classified using the naming of the existing capacitive sensing systems.

The summary of the physical layer of Passive Electric Field Sensing and of related technologies represents the groundwork for the upcoming sections. Due to the fact that this thesis discusses improvements of the measurement principle as well as hardware improvements to acquire Passive Electric Field data as well as optimizations for their signal processing, a fundamental understanding of the underlying principles is required.

After this explanation, the question arises of how it is possible to exploit these functioning mechanics of Passive Electric Field sensors to improve their deployment cost. The term deployment cost in this case includes on one hand the actual deployment of Passive Electric Field sensors and the user experience while the deployment takes place on the other hand. A sensor that can be used more quickly due to its user-friendliness requires fewer man-hours and therefore incurs lower personnel costs. That leads us to Research Question 1, which will be discussed in the next chapter.

3. Reducing deployment cost

In the last chapter, we discussed the terminology of Passive Electric Field Sensing as well as the physical principles behind this technology. While it is possible with this information to build such sensor systems, it is yet unclear how one can implement them in such a manner that the deployment of Passive Electric Field sensors can be handled with ease. The ability to quickly collect data is a key factor in the areas of academical and industrial research, as it empowers a user to reduce the time cost for setting up experiments and conducting them faster.

For this reasoning, the goal of this chapter is mainly to cover Research Question 1:

Research Question 1 Can Passive Electric Field data be collected in a manner that improves usability and deployment cost?

To measure Passive Electric Field data effectively, there are several aspects that will have to be further investigated. Because this work focuses on ubiquitous and environmental perception, an important issue is the integration of Passive Electric Field sensors in a pervasive way. To be more specific, this means to empower these sensor to be able to reliably perform measurements without the need of external power supplies as well as external measurement references (e.g. grounding connections). This is why in the first part of this chapter, a way for eliminating the ground reference will be presented for Passive Electric Field sensors. With these premises, it will be possible to hide Passive Electric Field sensors in a matter of seconds without the need of run cables to the locations of sensors and therefore accelerating the process of designing experiments with these sensors. Removing the need of a ground reference thus means to increase the flexibility of application of the sensors.

Another important aspect besides the ubiquitous integration of Passive Electric Field sensors in the human environment is the ability to quickly design and evaluate experiments with this technology. Normally, to design an experiment, a critical task is the definition of the measurement system. This includes human resources, where and what to measure as well as the used equipment [2]. To speed up this process, this chapter introduces the Linoc development toolkit. The main focus of its designed was to fit numerous use-cases while preserving the possibility for advanced users to change all system aspects. All features of this toolkit were built to ensure fast and easy design for experiments addressing electric field topics on the top level, without loosing the ability to overwrite configurations or code that was meant to give non-sophisticated users a faster and easier experience.

Since many use-cases depend on a bigger collection of data an hence on a bigger number of sensors, the question arises how many sensors are necessary to cover relevant areas of interest. Since this question cannot be answered universally without defining more precise circumstances or without defining the exact use-case, this chapter will cover this topic by comparing the performance of several different sized sensor setups while recording a wide variety of activities of daily life. This strategy will ensure to maximize the significance as high as possible.

3.1. Eliminating the Ground Reference

This section is based on the previous publication [B.1.4].

The Internet of Things is growing fast. More and more IoT applications are developed every day. According to Kahn et *al.*, two of the key challenges of the IoT are information privacy and to make network devices as energy efficient as possible [40]. But to accumulate more user information, many systems use sensor technologies that compromise the privacy of a user in various ways. With microphones and cameras, controlling a device can be achieved through voice commands and gestures. But these sensors are capable of delivering more information than just the needed control commands, like the identity of the users or the classification of their actions in the environment.

This is why the capacitive technology is a good fit for IoT applications. Their range is limited and it is harder, yet not impossible, to identify users. The most popular capacitive technology to identify users are dedicated capacitive fingerprint sensors. But, as shown by Holz et *al.* [34], even touchscreens can be used for this purpose. One could also use the impedance of a user to the environment, realized with a sweep over different AC frequencies, as shown by Harrison et *al.* [33]. However, most of these capacitive technologies that concern the privacy of users have a touch detection range. Even if capacitive systems are able to identify users over a larger range, as shown by Grosse-Puppendahl et *al.* [26], they do not invade the privacy of a user as much as optical or acoustical systems because the identification of a user is depending on wearing the same footwear.

The privacy concerns of a user are important, but so is the electric power consumption of an IoT technology. Systems that require a lot of energy are bound to locations with power outlets and power lines to supply themselves. This argument is another reason why capacitive sensors are effective for modern IoT applications. They can be implemented with very low power requirements. An example of an ultra low power human body motion sensor was made by Cohn et *al.* [12]. They used static electric field sensing, which in this paper is called passive capacitive sensing, to implement a wearable device that uses 3.3 μW for measurement.

A typical value for the range of capacitive sensors are 0 to 50cm [25]. There are some capacitive systems that scale up to 200cm, as shown by Iqbal et *al.* [37]. But these systems use more complex circuits and multiple amplifier stages, which are not suited for low power and thus mobile applications. Mobile Applications are needed to make up for the limited range of these sensors. Scattering multiple small sensors gives us the same effective detection range, but without the needed calibration as for the long-range sensors [37].

A big drawback of mobile capacitive sensors is the missing ground reference. As explained later in section 3.1.1, a ground reference is needed for capacitive measurement. The optimal ground reference is a wired connection to the ground, which contradicts the idea of a mobile use case. That is the reason why we, later on, present a possible setup for passive capacitive sensors, that don't need a ground reference.

3.1.1. "Classic" Active Capacitive Sensing

There are several active capacitive measurement so-called "modes". All active capacitive system have in common that they actively create an alternating electric field by charging and discharging conductive surfaces. For brevity and because the underlying physical principals are the same, we will only discuss Loading Mode.

Figure 3.1 illustrates the basic circuit of a Loading Mode setup. The output of the sensor is the time that is needed to do a charging and discharging cycle of C_1 (since fully charging an ideal capacitor would take an infinite amount of time it will only be charged to a certain percentage). The current that charges the electrode (p_1) is constant, but the distance between the user and the electrodes varies. The capacitance of C_1 is derived by

$$C_1 = \epsilon_0 \epsilon_r \frac{A}{d} \tag{3.1}$$

where C is the electrical capacitance of C_1. A is the area of the hand of the user or the area of the electrode (whichever is smaller) and d is the distance between them. ϵ_r is the permittivity of the material between user and electrode (for air, $\epsilon_r \approx 1$) and ϵ_0 is a constant value.

So, by measuring C_1, a capacitive sensor is able to approximate the distance of a user nearby.

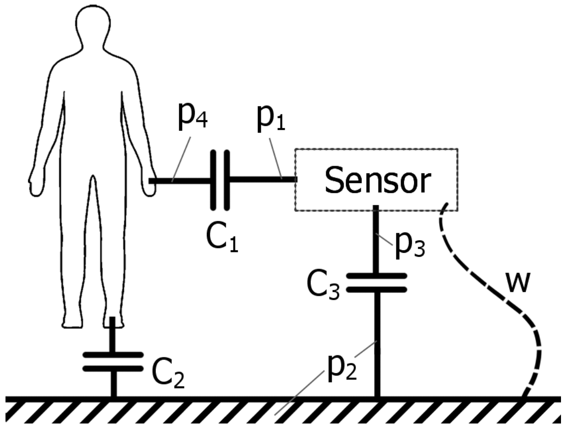


Figure 3.1.: Wireless systems do not have the direct connection (w) from the electrical ground potential (p_3) to the real ground potential (p_2).

3.1.2. Passive Electric Field Sensing

Passive electric field sensing is based on the same physical principals. The main difference between Active Electric Field Sensing and Passive Electric Field Sensing is that the passive technology doesn't actively charge and discharge the electrode. Passive electric field sensing measures the displacement current that is generated in the electrode by a statically charged, moving object.

A simple comparison for this effect is moving a charged rubber balloon along human hairs. The hair starts moving to the balloon. But in our case, the human hair is replaced by copper wires or copper plates. Since copper is conductive, it doesn't move towards the balloon, but the charged particles inside the copper (free electrons or electron holes) do. In other words - an electric current is created.

The principal setup for a passive electric field sensor is the same as shown in Figure 3.1. But this time, the voltage from potential p_1 to potential p_3 is measured. Since

$$Q = CU \tag{3.2}$$

where Q is the charge of C_1, C is the electrical capacitance and U is the voltage, we are able to measure C_1. Let us assume that, for simplicity's sake, the charge of C_1 is constant. This may only hold true for a short period of time. Sooner or later, the charge on C_1 will change due to triboelectric charging, which occurs naturally on every person through friction.

By measuring U we can now calculate C because Q is constant and thus again approximate the distance of a user d as shown in section 3.1.1. To put it simply, the current that flows from p_1 to p_3 indicates the distance of a user. Please note that a current only flows in closed circuits. In our case the closed circuit is build up by C_1, C_2 and C_3. That is why changing the capacitance of C_2 (the user lifts their feet) or C_3 (the sensor is moved) will have a similar effect as changing C_1 (the user moves towards/away from the sensor).

3.1.3. Proposed Solution

Instead of using operational amplifiers to detect user activities, we will use an instrumentation amplifier. Operational amplifiers for passive capacitive systems have been used in ambient assisted living before, as seen for example by Fu et *al.* [17] or in the Platypus system [26].

Instrumentation amplifiers in the domain of electric field sensing are currently used for ECGs [86]. Matthies et *al.* are showing an application for a type of ECG to evaluate facial expressions. But these use cases for activity classification with electric field sensing are bound to touch range.

With operational amplifiers, an often used setup for passive electric field sensors looks like shown in Figure 3.4a. An example of this setup is given by Harland et *al.*, which are using an equivalent setup to detect electrical human body activity [32]. But this setup has a dependency to the ground reference.

By using an Instrumentation Amplifier, which uses four inputs, we can effectively eliminate the need for a ground reference. Figure 3.4b shows a simplified circuit of an activity sensor. The output of the instrumentation amplifier can be derived as:

$$V_{out} = (V_{in1+} - V_{in1-}) - (V_{in2+} - V_{in2-}). \tag{3.3}$$

In our case, when the instrumentation amplifier is connected as shown in Figure 3.4b, this results in:

$$V_{out} = (p_{ant1} - p_{Vss}) - (p_{ant2} - p_{Vss}), \tag{3.4}$$

where p_{ant1} and p_{ant2} are the electric potentials of the electrodes and p_{Vss} is the ground potential. Hence:

$$\Leftrightarrow V_{out} = p_{ant1} - p_{ant2}. \tag{3.5}$$

Note that this formula is simplified since no amplification or other internal effects of the instrumentation amplifier, such as the reference voltage, for example, are modeled.

As demonstrated, connecting the ground potential to both sides of the instrumentation amplifier will remove it effectively.

3.1.4. Comparison of Grounded and Not Grounded Sensors

We gathered data from the discussed two sensor types to compare them to each other. The hardware that was used as well as the experimental setups are discussed in the following. We will begin with the design of the evaluation to compare the performance of the sensor types in question.

To evaluate our solution we conducted the following experiments. We used a classic passive electric field sensor which is implemented with an operational amplifier to compare it to our solution with an instrumentation amplifier. We want to test the detection range of human activities. The experimental setup consists of different markings on the floor which are indicating different distances to the sensor. We evaluated four different sensor setups in our experiment to show that grounding is the key factor of electric field sensing technologies with operation-amplifiers. These setups were placed on a small table in front of the marks on the floor. Figure 3.2 illustrates the evaluation.

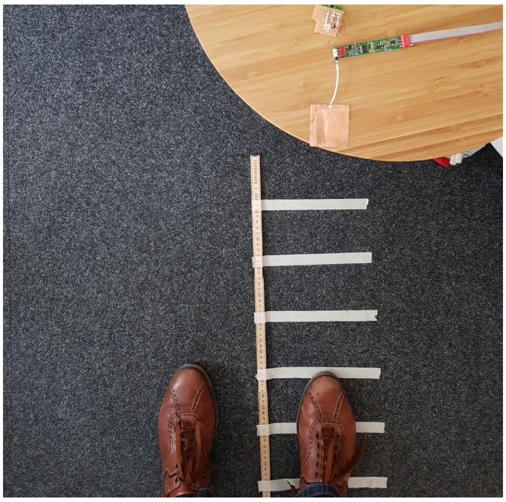


Figure 3.2.: Evaluating the range of the setups.

At the beginning of the test, the charge of the participating person will be normalized to eliminate outliers for more reliable results. These outliers can be caused by big accumulations of an electrical charge. Just by sitting in a chair for a longer period of time and constantly rubbing on the back of the seat can accumulate very high charges. This would lead to seemingly huge detection ranges of the sensors. To normalize the charge of a person, the person has to touch a grounded wire. This will drain most of the charge. In a realistic scenario however, a person will carry a certain charge. Therefore, the person has to walk a small distance to accumulate new charge, which is generated by the worn cloth and shoes rubbing to each other and rubbing on the floor.

A person is standing at the distance marker with the biggest distance (2,5 meters) to the sensor setup. Then the person has to lift one foot after another, as high as the knee. This will simulate the electrical behavior of step. With this test design, the simulated steps will be more similar to one another because a person cannot vary this movement as much as a natural step.

Then, the person has to move forward 10cm to the next mark on the floor and lift their feet again. This will be repeated until the sensor detects the moving person. Every sensor is rigged to a LED which indicates that an activity was detected.

This procedure is repeated for every of the four different sensor setups. The experiment was conducted with 16 different people. Every person had to activate every sensor setup twice. The setups are build up as follows:

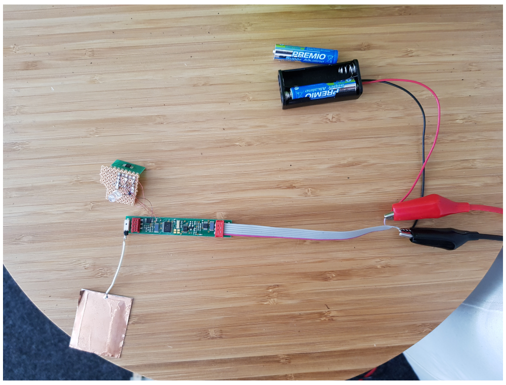
1. The first setup consists of an electric field sensor with an operation-amplifier. The sensor is hooked up to an external power supply with 3V. Hence, the sensor posses a direct connection to ground through the power supply (see Figure 3.3a).

2. The second setup consists of the same sensor as the first setup, but this time the sensor is powered by two batteries. The voltage of the two batteries is, as in the first setup, 3V (see Figure 3.3b).

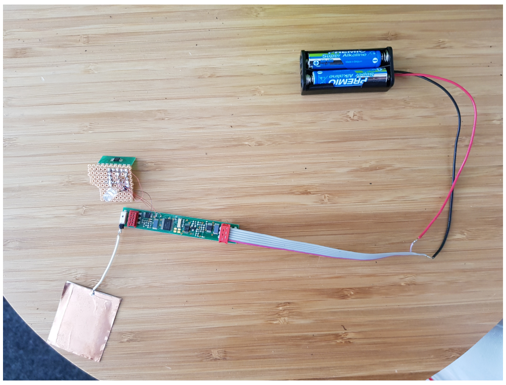
3. The third setup is similar to the second one. The only difference is that, additionally to the battery pack, the sensor is connected to the negative supply cable of an external power supply. This means again that the sensor is grounded, but receives its power from the battery pack because the positive terminal of the power supply is not connected (see Figure 3.3c).

4. The last setup evaluates an electric field sensor build with an instrumentation amplifier. The sensor is powered by a single 3V coin cell and has no ground connection (see Figure 3.3d).

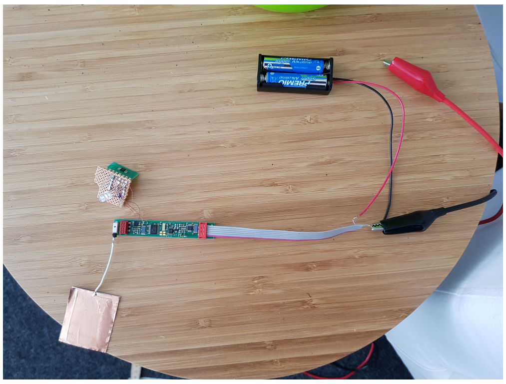
The sensing electrodes of all setups have the same size. But because the last setup consists of an instrumentation amplifier that measures human activity in a differential way, the last setup has to have two electrodes.



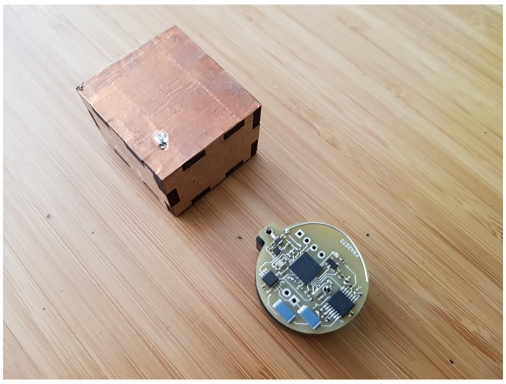
(a) Sensor with operation-amplifier and external power supply.



(b) Sensor with operation-amplifier powered by batteries.



(c) Sensor with operation-amplifier powered by batteries and ground connection.



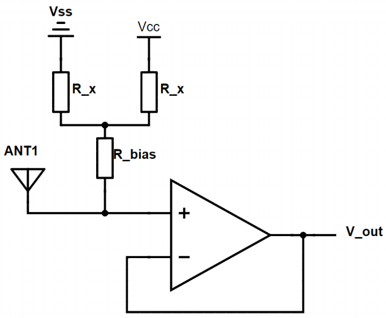
(d) Sensor with instrumentation amplifier.

Figure 3.3.: The different sensor setups.

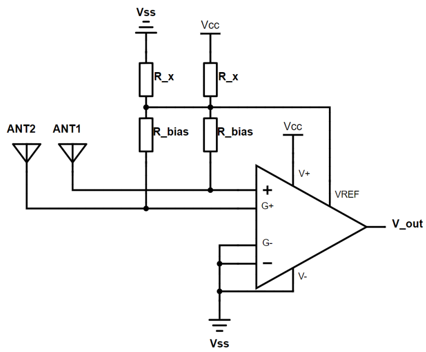
3.1.5. Hardware

The basic circuits of the sensor with operation-amplifier are illustrated in Figure 3.4a. Figure 3.4b shows our approach with instrumentation amplifier. A human activity will be detected if the sensor output is over approximately 60mV of $\frac{V_{cc}}{2}$. This functionality is realized with a simple comparator.

As indicated in Figure 3.4a and Figure 3.4b, both circuits have very a very high impedance connection to $\frac{V_{cc}}{2}$. This assembly group prevents long-lasting railing of the sensor output to V_{cc} and V_{ss} because it will slowly but steadily pull the sensor output to



(a) Circuit of an electric field sensor including an operation-amplifier.



(b) Circuit of an electric field sensor constructed with an instrumentation amplifier.

Figure 3.4.: Comparison between the used sensors.

$\frac{V_{cc}}{2}$. Decreasing the resistance of R_{bias} will improve this behavior even further, but at the cost of sensitivity. If R_{bias} is too low, no activities can be detected at all.

The power consumption for the measurement module with operation-amplifier is about 100μW. For our approach with instrumentation amplifier, 40μW are needed according to its data sheet to power the measurement module.

3.1.6. Results

Figure 3.5 illustrates the data resulting from the experiments described in Section 3.1.4.

We can conclude that it makes little to no difference for a sensor to use a normal external power supply or batteries. The arithmetic mean value of the sensing distance for a sensor built with an operation-amplifier a connected to a power supply is 65cm, with batteries and a connection to ground 67cm. The overall sensing distance of the sensors is high as the first and third quantiles of the box plot already suggests. The standard deviations of the sensing distance are 33cm (with power supply) and 36cm (with batteries and ground connection). The maximum detection range for both setups is 130cm.

When connected only to a battery, with no connection to the ground, the sensor with operation-amplifier performs much worse. In average, a distance of 34cm was measured, which is half of the sensors original performance when grounded, with a standard deviation of 23cm.

When an instrumentation amplifier is used, the average detection range is 182cm, the

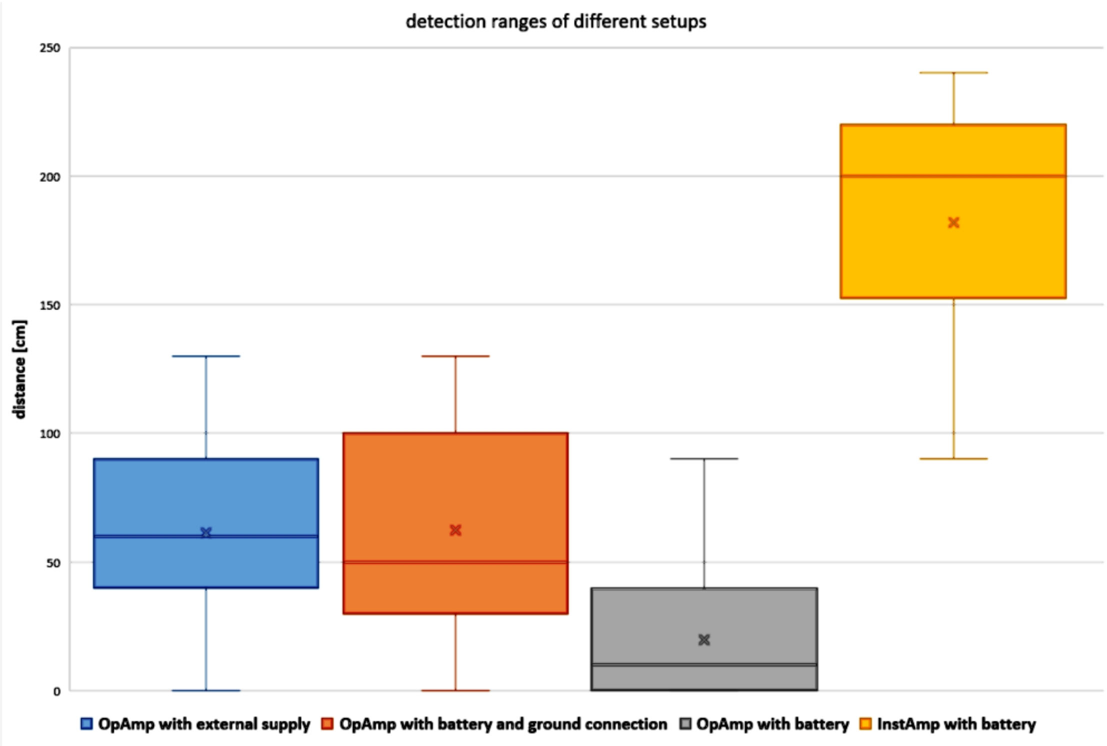


Figure 3.5.: Comparison of the different sensor setups. Indicated for each sensor are the minimum and maximum value, the first and third quantile and the median.

standard deviation is 46cm. This detection range is achieved without any connection to ground.

As already mentioned, the standard deviation of the detection ranges is high, which would indicate that the sensors are quite unreliable or the tests are not conclusive. But this high standard deviation is the result of a strong influence of the test persons. The worn clothes and more important the shoes of the persons have a high impact on the sensor performance.

So, we calculate for each person the differences between each setup and then we transfer the mean value of this differences per setup in the following confusion matrix Table 3.1.

The setups compared for every person are very conclusive; In 93% of the cases, setup 3.3a (external power supply) detects a user earlier than setup 3.3b (batteries). On average the advance is 42,3cm as shown in Table 3.1. Our solution, setup 3.3d even detects every

	setup 3.3a	setup 3.3b	setup 3.3c	setup 3.3d
setup 3.3a	0	-42,3	0,3	119,4
setup 3.3b		0	42,6	161,6
setup 3.3c			0	119,0
setup 3.3d				0

Table 3.1.: The mean average difference of the setups (as named in Figure 3.3). All values in [cm].

single person ahead of all other setups by more than a meter.

To conclude, the detection range of the sensors has a high average deviation. But still, the sensor ranges can be clearly ordered. Battery-powered sensors based on operation-amplifiers have the smallest detection range, sensor setups that are grounded have medium detection ranges and sensors based on instrumentation amplifiers perform best.

3.1.7. Short Summary

We briefly introduced the physical principles of active capacitive measurements and passive capacitive sensing to point out why the ground connection of these sensors plays an important role for the measurement circuits.

Then we presented a solution to this problem and it was shown that our approach to eliminate the ground reference for electric field sensors has big advantages over implementations with operation-amplifiers. The detection range of human activity nearly triples while the energy consumption of the measurement group is cut in half. Hence, when implemented with instrumentation amplifiers, electric field sensors are well suited for applications in ambient intelligence.

With this advanced sensor design, the next step is to increase the usability of this technology to be able to collect bigger chunks of data in different use-case scenarios.

3.2. Linoc: A Prototyping Platform for Capacitive and Passive Electrical Field Sensing

This section is based on the previous publication [B.1.1] as well as on the upcoming journal publication [B.2.3].

When it comes to prototyping with any kind of sensors, the most common ones can be connected via intra-board bus protocols such as I^2C, SPI, UART or JTAG-programmers.

This often requires programming skills and knowledge of embedded systems in order to work with the sensor data. Many sensor suppliers attempt to reduce the amount of programming needed, by supplying libraries or other interfaces to open source platforms like Arduino or Raspberry Pi.

However these platforms or libraries often lack advanced features and prevent programmers to access many in-depth parameters or functions, making them unsuited for more complex projects.

Rapid prototyping has made its way into research and design processes and accelerates the adoption of new techniques and concepts. The Linoc rapid prototyping toolkit is designed to provide an easy to use platform to be used in future projects for easy data acquisition. With this in mind the requirements for the firmware of the Linoc prototyping toolkit are on one hand the ease of usage and on the other hand the possibility for further refinement for advanced use cases.

The board has two measurement groups each for capacitive sensing and for Passive Electric Field Sensing. Both measurement principles are primarily used to detect activity, proximity and movement, each method performing differently depending on the ambient conditions. It is assumed that the Linoc board in most cases will be used mainly as a sensor whereas signal processing as well as higher level interactions are done on a separate computer. For this the setup and configuration procedure needs to stay as simple as possible. If then for example a demonstration was successful and the next step is to eliminate the need for a separate computer, the firmware design needs to allow modular extensions to be integrated. Only at this point knowledge of C programming and embedded systems is required.

The aim of the Linoc prototyping toolkit is to provide easy interfaces for data collection, setup of sensor networks and configuration of the board, while preserving the possibility to easily customize the source code to satisfy advanced use cases. To obtain larger sensor arrays, multiple Linoc boards can be connected to form a sensor network. One device will then take the role of the master to aggregate sensor data of multiple slaves before posting them to the server or host computer via USB or a wireless technique. This chapter begins with an overview of the role of toolkits in the modern design process, presents related work in the field of human computer interaction and proximity sensing alongside the actual hardware design of the Linoc toolkit. The Linoc hardware is detailed in Section 3.2.3 followed by the firmware design and its components, alongside information about challenges, limitations and design choices during the implementation process. Later on, the toolkit is evaluated with statistical methods as well as an example project implementation, demonstrating the toolkit's fast prototyping capabilities. A use case study will determine its usability.

3.2.1. Background

There are a couple of toolkits that can be used for interactive touch applications in the HCI area available. In this section, we summarize them and compare them with the Linoc rapid prototyping toolkit.

Hamblen et *al*. [31] describe the process of building a prototyping toolkit for future student works. They provide a cloud based compiler to their students to eliminate setup time and provide documentation in form of a wiki. The cloud based compiler is an attractive way to eliminate platform dependencies and can be hosted cheaply on even weaker computing platforms like single board computers. However, this poses a problem for rapid prototyping because the first step in using this toolkit is always to create a setup on a breadboard before sensor values can be read in.

WatchConnect [35] is a toolkit to develop cross-platform applications to explore interactions between the smartwatch and a second screen. The sensor data as well as the smartwatch's screen are used to extend classic input methods, but this also means that the use of the toolkit always requires a screen and therefore cannot be applied to any surface.

The Proximity Toolkit [46] provides an open-source hardware setup, interfaces to access higher-level proximity representation and a tool for visualization to use in proximity aware applications. It is designed to be hardware oblivious, so that different sensor techniques can be used. It focuses on the interaction with digital devices and provides developers with information about "orientation, distance, motion, identity and location information between entities", which are the dimensions for proximity in ubiquitous computing defined by Greenberg *et al*. The authors state that their motivation is to address the initial problem to acquire proximity sensor data for developers. Even if sensing hardware is available, effort is still required to translate sensor information into proximity, as calibration and noise can have a big impact. Their setup differs from the Linoc prototyping toolkit context as this toolkit is designed to require no counterpart in sensors or devices to work. Furthermore Linoc aims to be unobtrusive whereas the proximity toolkit focuses on intended interactions.

Midas [65] is a toolkit introduced by Savage et *al.* to design flexible capacitive touch sensors to apply to other objects in order to enrich interaction possibilities. While their focus lies on touch interactions it might be interesting to use their toolkit for electrode design. The evaluation was done in a way that the participants received a task to complete. They received feedback that videos can convey certain instructions better than images and addressed this by adding animations.

The CapToolkit [89] is the second generation of capacitive toolkits by Wimmer et *al.*. A stated goal is to make implicit interaction concepts easier to develop. It supports up to eight Loading Mode sensors, as shown in Figure 3.6 with a sampling frequency between

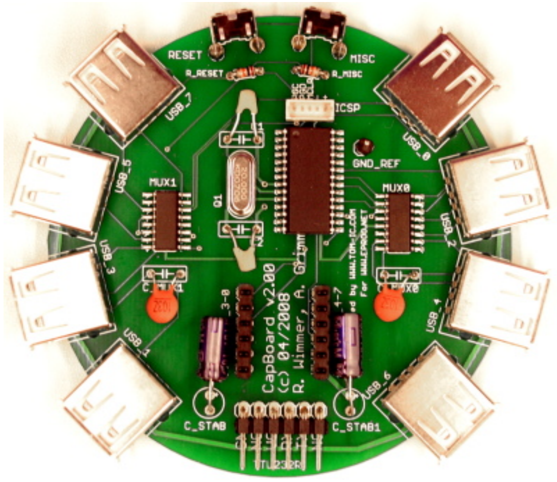


Figure 3.6.: Captoolkit by Wimmer et *al.* [89]

25Hz and 100Hz. Sensor reconfiguration is possible at run-time using a custom protocol via USB connection. UDP and TCP interfaces can be used by the connected host computer. The Linoc prototyping toolkit provides this functionality directly by the sensor board, which is made possible by recent microcontroller development. Thus these interfaces can still be used with battery powered sensors without physical connection to a computer. With a 10cm x 10cm electrode the CapToolkit is able to detect a human body at a distance up to 1m and hand movements up to 50cm. The spatial resolution is given at 1cm at 25cm distance, but was not reproduced in experiments by Puppedahl et *al.* [24].

The OpenCapSense (shown in Figure 3.7) board is inspired by the CapToolkit and addresses three shortcomings: confinement to Loading Mode capacitive measurement, slow sample frequency and no options to connect multiple sensor boards. The last aspect is overcome by providing two CAN real time bus interfaces to synchronize data. The board features eight USB ports for external capacitive sensors and a framework for data exchange. It supports different sensor types, and has been used with the three different capacitive measuring modes, as well as passive electric field sensors [28]. It operates at frequencies up to 250Hz with eight and up to 1kHz with one sensor attached [24].

The OpenCapSense board is in a way the direct predecessor of the Linoc prototyping toolkit and has been used in various research projects [4] in the HCI area. It was originally designed by Tobias Große-Puppendahl. It is thus closest related in application purpose, albeit having a different sensor concept. Linoc also focuses even more on usability than

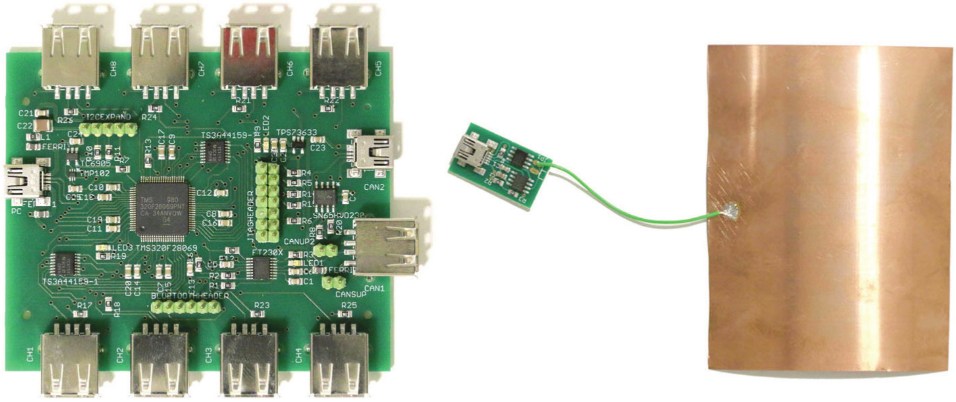


Figure 3.7.: OpenCapSense by Puppedahl et *al*. [25]

OpenCapSense and was designed with a more modern processor and more possibilities to connect the sensor to a computer.

3.2.2. Design Process

Before describing the actual hardware and software, we will briefly discuss the design process of the Linoc prototyping toolkit. The design process was structured with several design goals in mind. Linoc was built to be fitting for a wide variety of use cases. That is why it should meet the following requirements, that are referred as design goals further on.

1. High connectivity
2. Easy to use
3. Support for multiple programming languages
4. Realization of advanced use cases possible
5. Chaining of multiple boards

Design goal 1 was the main reason to create Linoc. While many available toolkits have multiple interfaces, most of the time additional hardware is needed if more than a

USB connection is required, for example a wireless connection. This leads to more effort required while building an actual prototype both for hardware and software development.

An easy to use user experience as stated in design goal 2 is very important if the toolkit is to be used in an academic environment. This will enable students and teachers alike to use Linoc seamlessly in every kind of project. It also reduces the amount of time that users need, both experienced and inexperienced ones, to get their hands on the first data.

While most toolkits require a certain programming language to use them, Linoc was designed so that it can be programmed in several languages, because it is time consuming hassle to be bound to a certain language that the user might not prefer. With the freedom to choose the language as stated in goal 3, the user is empowered to use the language he is most capable of and that is most fitting for his current project.

Having a toolkit that is easy to use should not limit the number of use cases you can use it for. In many cases, easy usability restricts versatility. To prevent Linoc from being a prototyping toolkit only for beginners, we included design goal 4.

Another important aspect learned while using other toolkits was, that no matter how many sensors can be attached to a board, there is always a use case where you need more. While some toolkits like OpenCapSense have a CAN-bus interface to combine multiple boards, it is still a task that takes up several hours to connect and reprogram them. That is why we added design goal 5. In this way, the user is able to acquire higher dimensional data by adding more sensors.

After explaining why we choose these design goals, we will now focus on how we implemented them in hardware and software.

3.2.3. Microcontroller

The microcontroller used on the Linoc board has to fulfil several requirements; The choice of the microncontroller is a critical step because most of these requirements have to be covered by the controller itself. To be precise, the controller affects the design goals 1, 3 and 4. The ESP32 from Espressif fulfills all of these requirements. It features Wi-Fi, Bluetooth and Ethernet connectivity as high level protocols. For intra-board communication, the user can choose between several low level protocols such as UART, I^2C, I^2S, CAN and SPI to name only the most common ones. This makes the ESP32 a good processor for our needs of high connectivity. The ESP32 has enough memory to support a real time operating system such as FreeRTOS. This allows for complex use cases as we planed in goal 4.

Since the ESP32 is the direct successor of the ESP8266, which was (and still is) very popular in the maker-scene and for IOT products, there are a couple of toolchains for different programming languages available.

Toolchain	Language	Editor
ESP-IDF	C/C++ with FreeRTOS	Eclipse IDE
Mongoose OS	C & JavaScript	Browser page
MicroPython	Python	-
PlatformIO	C/C++	Atom editor, Eclipse IDE, Visual Studio Code, ...
Arduino	C++	Arduino IDE

Table 3.2.: Programming languages and toolchains available for the ESP32

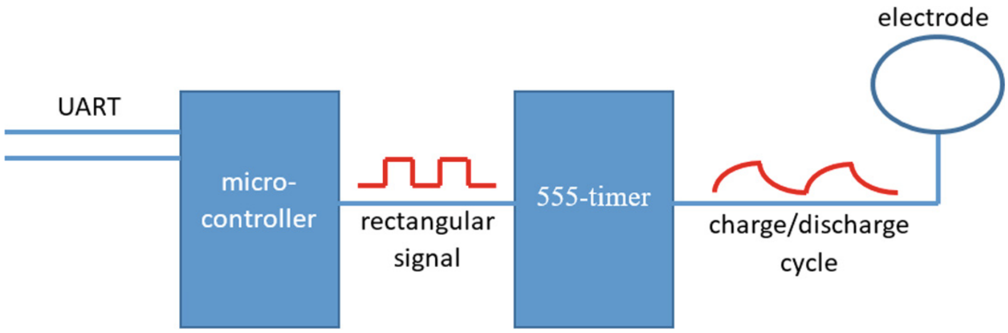


Figure 3.8.: Simplified model of the capacitive sensor

Table 3.2 lists a selection of possible languages and editors for the ESP32. Note that this not only is in favor of our design goal 3, but also goal 2. This is because the ESP32 is, amongst others, also Arduino compatible. Arduino is a commonly used language by beginners when it comes to embedded programming.

3.2.4. Capacitive Loading Mode Sensor

The Linoc prototyping toolkit features two capacitive Loading Mode sensors. The sensors were added directly onto the board, so that in contrast to other prototyping toolkits, there is no need to add more external hardware.

The capacitive group's main component is the 555 timer which generates the charging cycles on the electrode, as shown in Figure 3.8, with a constant charging current. Since the current is constant, the charging process is influenced by the environment. When a conductive objects approaches the electrode, the resulting capacity between electrode and object increases. Hence, the time needed to charge this capacitor with the same amount of current increases. A pulse counter module in the microcontroller then counts the number of cycles per second, which is the final measurement parameter. The microcontroller is also able to dis- and re-enable the 555 timers so that it is possible to prevent cross talk when multiple sensors are active at the same time.

Linoc also features a shield for both capacitive sensors to support coaxial cable or to minimize environmental influences on selected parts of the electrode. The shield is realized by a simple voltage follower, implemented with an operational amplifier, of the capacitive feed line.

3.2.5. Passive Electric Field Sensor

Besides the two capacitive sensors, Linoc features two sensors for Passive Electric Field Sensing. The main differences between a capacitive Loading Mode sensor and Passive Electric Field Sensing are the detection range, the mode of operation and the energy consumption. Passive Electric Field Sensing can detect moving conductive objects in a distance of up to two meters [78], while the range of capacitive sensing in classical Loading Mode is limited to about 35cm (see 3.2.10). A Loading Mode sensor measures the capacity of a virtual capacitor that is created between electrode and user, whereas an passive electric field sensor measures the induced current that a user can transmit through the same virtual capacitor between electrode and himself. This also implies that the passive electric field sensor of the Linoc toolkit is only able to detect movements, while the Loading Mode sensor is capable of sensing non-moving objects.

The last difference is the energy consumption which is lower for passive electric field sensors, but since the microcontroller used on the Linoc board draws far more power than all sensors combined and because the Linoc toolkit is designed to be used with a USB connection or a USB powerbank, this is not a crucial point of the toolkit discussion.

3.2.6. Board Layout

Since one of the main goals in mind while designing the Linoc prototyping toolkit is fast data acquisition, the board features numerous connection types. The Linoc prototyping toolkit can sent data over various protocols, as well as raw binary data, as shown in Table 3.3.

Figure 3.9 clarifies the location of all connectors. The prototyping board also has three free programmable LEDs as well as a free programmable button. The second button of the board is hard wired to reset the microcontroller.

Protocoll	Connector
Wi-Fi (b/g/n)	2.4GHz antenna
Bluetooth	2.4GHz antenna
USB	front board connector
I^2S	left and right pinouts
UART	micromatch connector
Binary data over GPIO	left and right pinouts
Binary data over relais	left and right pinouts

Table 3.3.: Outputs and their correlating connectors

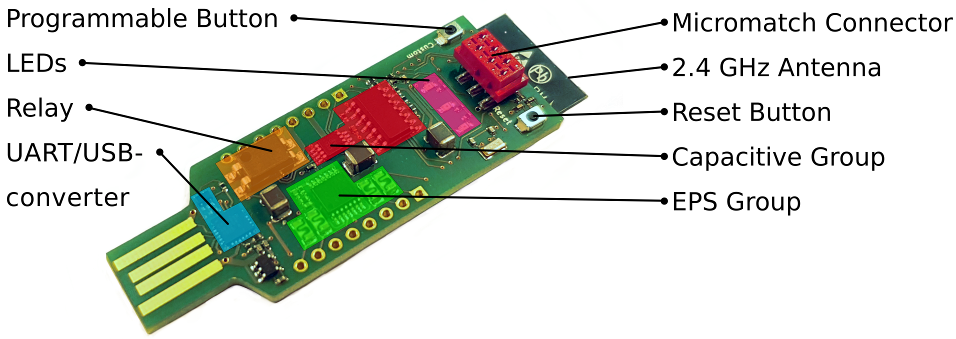


Figure 3.9.: Hardware layout of Linoc

A mosfet relais was added to the board (see Figure 3.9) to cover more use cases (see design goal 4) without the need of further soldering. The relais enables the user to directly connect LEDs, piezo buzzers or other hardware that requires more voltage and higher currents to the pin-header on the side of the board (up to 30V and 1A).

The micromatch connector was added for several reasons. Since the board should be capable of creating sensor chains, which was discussed in goal 5, a ribbon cable is a suitable solution. This is because, again, no further soldering is required when crimping new connectors to a ribbon cable. Ribbon cables can be configured with any number of connectors which can be spaced at any distance. The ribbon cable allows the creation of sensor networks by transmitting data as well as the power demanded by the sensors. This way, just a single power supply is needed for multi sensor setups.

Another important feature of the toolkit is the built in USB to UART converter. The converter is required to flash the microcontroller. By integrating it onto the board an external programmer, common to many toolkits, is not required here. Note that the connection over UART/USB does not support live debugging as JTAG adapters do.

3.2.7. Software

Central interface to the Linoc toolkit is a console over the UART bus of the microprocessor, which is connected to the USB interface. Without programming or flashing, the configuration of sensor groups, sampling frequency and sensor array configuration can be changed as well as wireless connections established and system diagnostics be printed. A help command lists available options. This is usually sufficient to use the toolkit in own projects and fulfills use case 2, because no further programming is required.

The software implementation is done with the ESP-IDF and FreeRTOS in the programming language C. This allows advanced users to access low-level functionality of the microcontroller in order to modify the software to their needs as aimed for in design goal 4. Multiple sensors can be connected to a sensor array (design goal 5) and communicate via I^2C with each other. After initiating the setup from the master device (the one connected to the users computer), the order on the array is established by pressing a button on the slave devices in the respective order. This allows for various physical setups.

The sensor data is transferred to the host computer via UART, or transmitted via Wi-Fi, either by posting to a given TCP server or by hosting a TCP server on the toolkit to which other entities can connect to (design goal 1). This data can then be further processed by the user with her preferred tools or programming languages (design goal 3).

3.2.8. Evaluation

To generate a meaningful and comparable evaluation, we choose to cover multiple categories identified in the meta study by Ledo et *al.* [44], in which evaluation strategies and common pitfalls were identified by analyzing 68 published toolkits for interactive systems. Thus we chose to evaluate in terms of usability, performance and demonstration.

3.2.9. User Evaluation

To evaluate usage, a set of tasks was devised for the participants to explore the functionality of the toolkit. The instructions besides setup, were vaguely formulated, to determine if the Linoc interfaces are designed intuitively and the information provided through the console sufficient. The advanced tasks were only given as concepts to provide some freedom for the participants to explore the toolkit. Following the set of tasks a Likert scale questionnaire was answered by the participants. The questionnaire is attached in Appendix A.1.

Age	24 - 39, Average: 30
Gender	Female: 4, Male: 7
Occupation	School: 2, Study: 6, Work: 3
OS used	Windows: 5, Mac: 2, Linux: 4

Table 3.4.: Participant information (age not reported by all individuals)

The study was carried out with eleven participants. More information about the participants and what operating systems they used is listed in Table 3.4. Most participants needed some time to familiarize with the toolkit and the way the commands work, but became more fluent over time. The majority of participants needed about 20 to 30 minutes to complete the survey.

The results of the questionnaire are presented in Table 3.5. The usage of the toolkit and even the complex task of setting a sensor array was reported as intuitive. Even participants reporting not experienced in programming or computer systems mostly did not feel overwhelmed by the system and a participant feeling overwhelmed in the beginning was able to finish the given tasks with some assistance. Note that, although inexperienced users also participated in the study, the focus of the study was on scientific employees, as the toolkit is also intended for rapid prototyping tasks in scientific environments.

Eight out of the eleven participants reported receiving assistance during the study. Nearly all participants were able to complete all the given tasks successfully. In most cases the assistance was limited to occasional clarifications, only two minor technical difficulties arose during the evaluation which resulted in receiving more assistance than just clarifications.

As the results of the evaluation in Table 3.5 show, the overall feedback is very positive. This is not only shown by the high marks but also by the low standard deviation, which indicates that the opinion of all participants are nearly the same. Application ideas for future projects as stated from the users in "Free questions" section of the questionnaire centered around general activity and proximity detection and integration to cloud computing.

3.2.10. Performance

To assess the performance of the Loading Mode sensors, the Linoc prototyping toolkit was mounted in an automatic test stand. The test stand consists of a metal box to shield from external influences and a conductive platform that is moved by a stepper motor. It can be lifted up to 35cm over the sensor.

All sensor values are recorded for several minutes, then the platform is moved upwards

Question	Mean	Median	STD
Experienced User?	1,91	1	1,6
Similar systems already used?	3,09	3	1,51
Tasks successful?	1,45	1	0,69
Feeling overwhelmed?	4,18	5	1,25
Usage intuitive?	1,82	1	1,25
Functionality sufficient?	1,09	1	0,42
Sensor array intuitive?	1,82	2	0,98

Table 3.5.: Results from the questionnaire, ranging from 1 (strongly agree) to 5 (strongly disagree)

1cm. For this test, the pulses of the 555 timer (see 3.2.4) were counted for 0,5 seconds, which corresponds to a sensor sampling rate of 2 Hz. This means that over 200 samples were collected for every position of the movable test platform.

It is possible to distinguish between two different distances of the test platform as long as the measured values don't overlap. A graphical representation with error bars was arranged, as illustrated in Figure 3.10, to visualize which distances were distinguished successfully and thereby concluding the maximal range of the system. To derive if a distance is distinguishable from the previous, following metric is used:

$$\bar{m_i} - \bar{m}_{(i-1)} - \sigma_i - \sigma_{i-1} > 0$$

Meaning that if the mean value of a distance $\bar{m_i}$ minus its standard deviation σ_i is still bigger than the mean value of the previous measured distance $\bar{m}_{(i-1)}$, including its standard deviation σ_{i-1}, all sensor values of these two distances can be clearly assigned.

In our tests, the maximal testable range of 35cm of the automated test stand was detectable with the Linoc toolkit, matching the performance of the OpenCapSense, as shown in Figure 3.10. Note that this test stand is shielded from environmental noise so that the detectable range can be lower in noisy environments. The big standard deviation, seen at a distance of 5mm in Figure 3.10, is the result of a settling time of the sensor. This is why the first values of the Loading Mode sensor can be observed as more noisy than values recorded later on.

Another impact factor of the sensor range are custom firmwares. A software which generates strong fluctuations in the energy demand of the processor will also destabilize the sensors power supply. Very CPU intensive tasks followed by a CPU idle time can induce such a behaviour. To prevent this issue, Linoc was equipped with large decoupling capacitors.

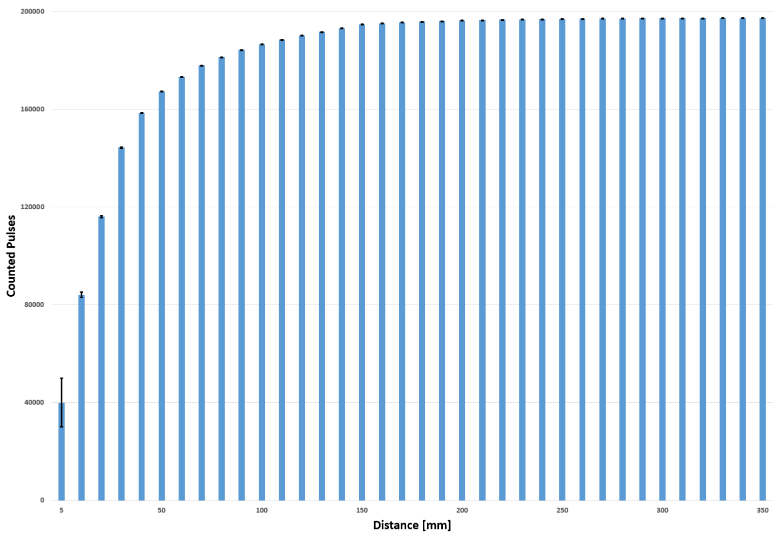


Figure 3.10.: Data of a test run in the automated test stand including the standard deviation

3.2.11. Demonstration - A Ten Minute Built of a Fluid Level Metering

CapToolkit [89] demonstrated a fluid level metering for a beer bottle with a 10cm x 10cm electrode. This demonstration was repeated using the Linoc toolkit for comparison. To ensure consistent results and to exclude the tester, he had to stay at a constant distance and allowing the signal to tune in after pouring out 4cl beer at a time. Otherwise it would have been possible that parasitic capacitances arise, forming alternative circuits from sensor to the probe over the tester to ground. A calibration curve similar to the one presented in [89] was measured and is shown in Figure 3.11.

Note that the unit on the y-axis differs from the usual unit throughout this paper. This is due to the fact, that Wimmer et *al.* measure the time of the capacitive charging cycles and not the frequency. The relationship is $t = 1/f$ and the absolute value determined by the sampling length.

3.2.12. Short Summary

In this section, the Linoc toolkit was introduced. Its main purpose is the fast and easy acquisition of Passive Electric Field data as well as data from Loading Mode measurements. To accomplish this fast and easy acquisition of data, the functionality of the

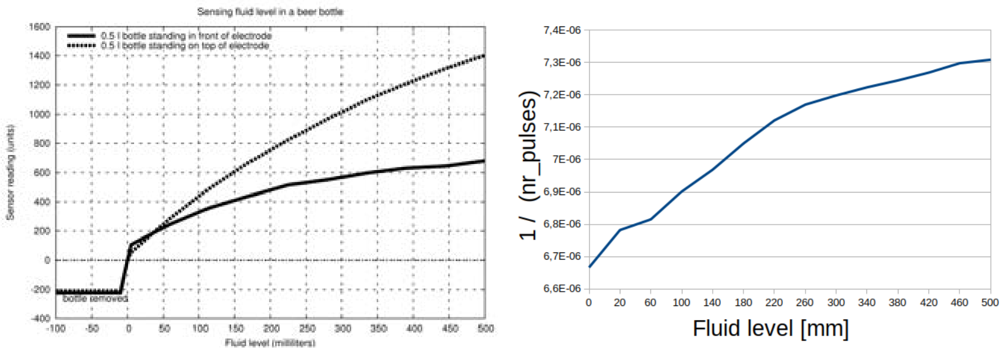


Figure 3.11.: Comparison of the fluid level metering in [89] ("sensor reading (units)" is plotted over "Fluid Level [mm]") and a reproduction using the same electrode and beer bottle on the right

introduced toolkit was built around five key requirements. While four out of these five key requirements are technical in nature and thus can be proven with functionality tests, the second requirement "Easy to use" was proven with a user survey with differently skilled participants. To summarize, this toolkit was built to contribute to RQ1 on how to collect Passive Electric Field data with an improved user experience in mind. With the Linoc toolkit, data acquisition for electric field sensing can be achieved in various manners, depending on the use case and its requirements. The toolkit is able to collect data from an arbitrary number of electrodes while maintaining its ease of use factor. In addition, the toolkit does not constrain the user to utilize a certain programming language since it was designed to support multiple options.

3.3. Evaluating the Number of Sensors Needed for Recognition of Daily Life Activities

This section is based on the publication [B.1.13].

Electric field sensors are used in a variety of ways to recognize different human actions and behaviors, for example, fall detection or classification of movements. However, very little is known about the number of sensors that are needed to achieve an acceptable recognition rate. Most systems just use as many sensors as possible to achieve confusion matrices with high true positive and true negative rates. In this section, the relation of recognition rates and the size of a system composed of Passive Electric Field sensors shall be further investigated. For this purpose, several setups to recognize different human activities will be created and evaluated, each with a varying number of sensor tokens.

3.3.1. Activities of Daily Life

Every day people carry out various activities. These take place at work, at leisure or at home in your own four walls. In modern era of pervasive computing researchers created a multitude of ways for activity tracking and activity recognition which are used and needed in many different application scenarios [49, 72, 30, 45, 7, 58]. Be it elder care in assisted living environments [72, 42, 7, 58, 75, 12] or medical purposes [7, 75], e.g. for diabetics [30], activity recognition can help. With the advent of modern computers and technologies, the possibilities for activity tracking and recognition are multiplied [45].

Various types of activities are investigated with a variety of diverse methods. New technologies were developed to help people plan their day, save electricity and energy, and make live easier. Apartments are becoming more and more networked and digitization is entering people's lives, at work as well as at home.

At work, activity detection monitors and optimized processes, provide resources and identify bottlenecks. New process planning methods enable employees to be deployed more quickly and selectively by identifying their workload.

In the private sector, almost everyone has a sensor with himself every day. Due to the constant progress in technology, the mobile phone has many sensors already built in, which make it possible to detect the current activity of humans [43]. New products were created to monitor a person's sleep. Thus, deep sleep phases and waking phases are recorded in order to find a suitable time for waking the person. Smart home technologies are used to make everyday life easier or to have a coffee right after a shower. Older, still self-employed people, can use sensors to detect falls or accidents so that they can be fetched by professional carers [72]. For this, however, sensors are required that work in a privacy-friendly manner, do not interfere and work with as little energy as possible. It is also a major challenge to detect activities in rooms of different sizes without adapting the sensor topology and detection method to various layouts of rooms and conditions. Sensors that can be freely distributed and assigned to detect activities of daily life would be helpful.

To successfully use sensors for the detection of activities, it is important to know the requirements placed on the sensors and their topology. Many jobs use as many sensors as possible to achieve the necessary detection rates. However, a lower number of sensors can be as efficient as the maximum number of sensors. Therefore, it is important to find out what kind of distribution and topology are important for the recognition of activities of daily life.

The aim of this section is to create different sensor setups for the recognition of various

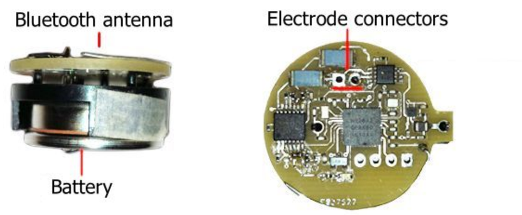


Figure 3.12.: ActiTag sensor front (left) and top (right).

Figure 3.13.: ActiTag sensor housing top-front (left), front-bottom (middle) and top opened with ActiTag inside (right).

activities and to vary their size and scope. The detection rates are then compared with the sensor setups and their sizes to give an overview for necessary sizes of these setups. The placement of the sensors is also considered in order to achieve the best possible knowledge gain.

3.3.2. ActiTag Hardware

The sensors used for this evaluation, later on also called “ActiTag”, are Passive Electric Field sensors which use a coin cell as energy source. I designed ActiTag to be compact enough to be hidden in compartments, under furniture or behind other objects. Another design goal was to keep maintenance of the sensors low by maximizing the lifespan of the battery cell. It builds on the measurement principles of differential Passive Electric Field Sensing, as explained in Section 3.1.

The electrodes of the sensor are pre-charged over a $1\text{G}\Omega$ resistor. This has two effects; The defined voltage level results in a known baseline of the signal. Further more, it reduces over saturation of the measured signal by continuously pulling the signal towards the pre-defined voltage level. The nominal voltage level on the electrodes is 1.65V, exactly half of the 3.3V supply voltage.

Another advantage of the pre-charged electrode voltage level is the possibility to use threshold voltage detection directly implemented with analog components. Analog components can increase the energy efficiency of a system because their operation can save the need of a micro controller or other energy intensive building blocks. That is why the sensor includes a simple threshold comparator circuit based on a operation amplifier, with a defined threshold slightly over 1.65V.

When the comparator circuit detects an activity, an interrupt on the micro controller is triggered to wake up the micro controller from its deep sleep state. The sensor then collects 40 samples at a 50Hz sampling rate and thus 800ms of data. All collected data is transmitted via Bluetooth Low Energy (BLE).

The package is sent without handshake procedure. No handshake was used to save energy and to distribute the packets of a large number of sensors without the need of a preceding pairing procedure, keeping the number of used sensors flexible. In addition allows sending the data without a handshake to use an arbitrary number of receiving stations. This enables even larger and more flexible sensor arrangements. However, it also means that anyone can intercept and evaluate the BLE signals because no encryption was used, which can be dangerous for privacy issues. The data collected is not stored by the sensor and therefore ActiTag works according to a tape and forget procedure.

All these previously mentioned methods combined ensure that the ActiTag sensors can work in a very energy-saving manner. The only relevant energy consumption occurs when sending the data packets via BLE.

3.3.3. Evaluation Conditions

The tests are carried out in a laboratory, furnished like an apartment, as depicted in Figure 3.14. It includes a bed room with bed, closet and TV, an open kitchen with oven and stove, pots, dishes and cutting boards. The living room has a sofa, side table, carpet and TV as well as TV cabinet. This ensures that the individual activities examined are typical for the respective living conditions.

All activities were performed by 15 test person (10 male, 5 female). Since the footwear and the respective soles have different insulating properties and the sensors measure charge shifts caused by charge carriers, it is important to take the different soles into account. If, for example, non-insulating shoes, such as ESD shoes[1], are worn, the electrical charge of the person immediately flows to ground again. Therefore, the person wearing these shoes cannot act as a load carrier to move charges of the electrodes, resulting in no

[1]ESD stands for ElectroStatic Discharge. These shoes are worn by people who work in environments where spontaneous discharges are not desirable, e.g. when working with microelectronics.

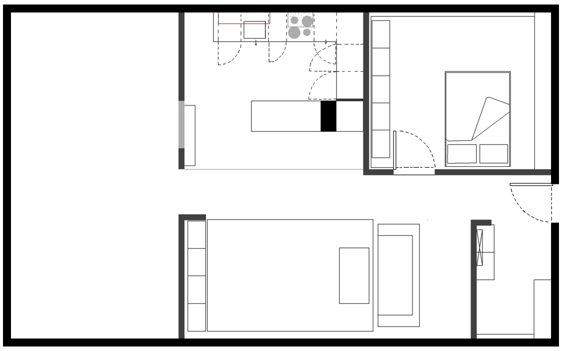


Figure 3.14.: Overview of the evaluation lab

measurable current at all. The majority of the test persons in these tests wore shoe soles made of rubber (12 test persons), followed by plastic (2 test persons) and leather with heel (1 test person).

Since the amplitude of the measured signal is depending on the amount of charge of a charged carrier such as a human, it is important that all test persons carrying out the activities in the respective areas have a reasonably equal charge. Therefore, every test person is first grounded and then walks over the laid carpet to the individual stations where the activities are carried out. This ensures that the now charge-free test subjects can recharge themselves electrostatically so that an ActiTag sensor can be triggered. This happens, among other things, through the triboelectric effect, which results from friction between two surfaces.

3.3.4. Test Procedures

This section will briefly describe the conducted experiments to evaluate different sized sensor setups. All conducted tasks were taken in the listed order.

To better organize the executed experiments and since the laboratory is constructed out of several individual areas, the list of performed tasks is categorized in kitchen activities, tasks performed in the living room and bed room.

Besides explaining the different activities, this section will also include sensor maps for the various rooms for the sake of repeatability, starting with the kitchen as shown in Figure 3.15.

- “Preparation”: Preparing a meal

  In the task “Preparation” the test person started at the bottom of the kitchen, next to

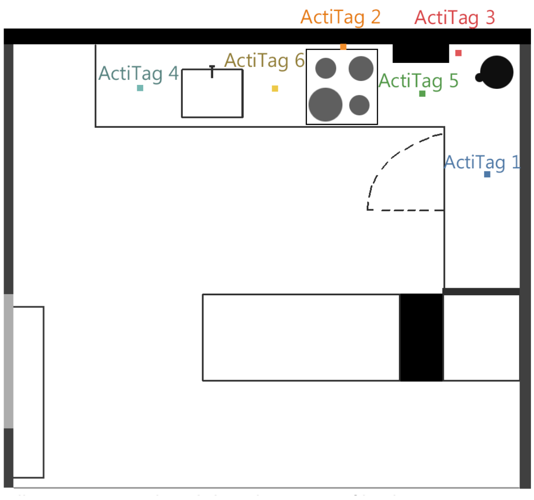


Figure 3.15.: Sensor placements in the kitchen

the kitchen table and walked past the sink and the stove to the kitchen cupboard to take out a pot and a pan and place them on the stove as shown in Figure 3.16b. Also a cutting board and a knife, as well as some toy dough in a plastic bowl to resemble food were taken out of a kitchen compartment. After the cooking utensils were placed on the stove, the dough was cut into pieces of any size (see Figure 3.16a). Finally, the cut pieces were distributed to the pan and the pot.

- "Cookpan": Using the cookpan

  The pan was touched and slightly moved. Also, the plasticine was moved and stirred in the pan with the spatula.

- "Cookpot": Using the cookpot

  The activity for using the pot was similar to the "Cookpan" activity, except that the lid of the pot had to be removed and the same spatula was taken out of the pan and stirred around in the pot.

- "Kettle": Using the coffee machine

  A coffee pot was first taken out of the coffee machine residing on the kitchen counter and brought to the sink to fill in water. Since the kitchen appliances are not connected to avoid wasting food for the test series, the coffee pot was only unscrewed, held under the tap and turned on for an independently selected time

(a) Simulated cutting food and cooking with dough

(b) Placing a pot, pan and spatula in the kitchen with sensors

Figure 3.16.: Movement sequences performed in the "Preparation" activity

(approx. 30 seconds) until it was closed again and the coffee pot was brought back to the coffee machine. The upper lid of the coffee machine was then opened in order to pour in water for the coffee preparation, after which the button of the coffee machine was pressed.

- "Cleaning": Cleaning the kitchen

  The last activity was cleaning up and washing up. At first, the dough was put from the pot and the pan back into the bowl and then the pan and the pot as well as the cutting tool were placed into the sink. They were wiped off with a dishcloth after the water was turned up shortly. After wiping, the utensils were put back in the cupboard.

The activities observed in the living room are listed in the following. The sensor setup for these tests can be taken from Figure 3.17.

- "TV Remote": Pick up and put back the remote control

  At first, the test persons were asked to take the remote control from the TV and go to the sofa.

- "Sofa Sit Down": Sit down on the sofa

  Arrived at the sofa, they had to sit down on the sofa for a short amount of time.

- "Sofa Stand Up": Get up from the sofa

  After a short break, the test persons were asked to stand up again and to put the remote control back to its place, which was in front of the TV.

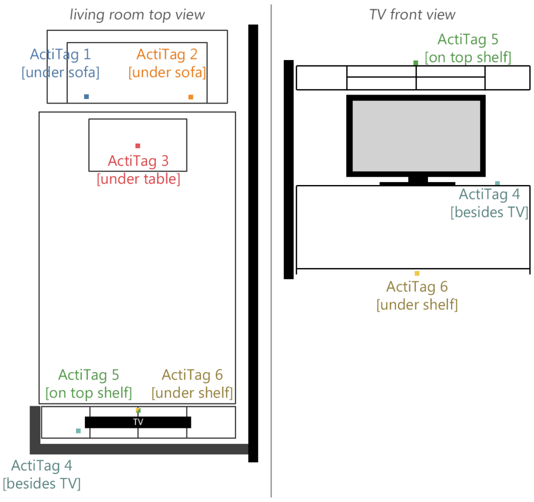


Figure 3.17.: Sensor placements in the living room, including a front view of the TV

- “Legs Up”: Putting the feet on the sofa

  Since the test persons had to stand in front of the television and the book shelf in order to put back the remote control, they were asked to take a magazine from the shelf and to return to the sofa. There, the test persons sat down again and put their feet up on the sofa.

- “Book”: Putting the magazine back

  After a short break the test persons stood up again and put the magazine back on the shelf.

At last, the sensor setup for the bed room is depicted in Figure 3.18. The examined activities were carried out as stated in the following:

- “Cloth Off”: Take off jacket and put it in the cupboard

  The test person started dressed with a jacket in the bed room door and walked along the bed and the TV to the cupboard, opened it, pulled out and folded the jacket and placed it in a cupboard compartment.

- “TV”: Taking or putting the remote control back

  The person had to move from the cabinet to the TV, picked up the remote control and sat down on the left side of the head of the bed.

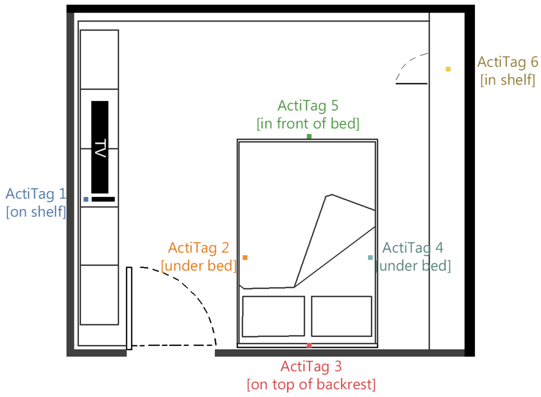


Figure 3.18.: Sensor map of the bed room

- "Lay Down": Laying in bed

  As the test person already sat on the bed, this activity merely included lifting up their feet and lying down onto the bed completely.

- "Turn Around": Rotate body in bed

  The activity of turning around in bed consisted of an arbitrarily large rotation to the right in the bed and a rotation back to the original position.

- "Get Up": Getting up from bed

  During this activity, the person got up completely again and reached the final position, standing in front of the left side of the bed.

3.3.5. Discussion

Since there are a lot of different sensor setups to consider, we will introduce a notation to distinguish between them. A sensor setup in our case consists of a maximum of 6 ActiTags. The enumeration of these can be seen in the previously discussed sensor placements in the kitchen, living- and bed room. The kitchen setup 2,4,6 for example is comprised of ActiTag 2, 4 and 6 as depicted by Figure 3.15. The data of the missing sensors 1, 3 and 5 will not be considered in setup 2,4,6.

The features considered are, on the one hand, the frequency of occurrence of sensors during certain activities and on the other hand the maximum value difference that has occurred in a measurement. Since a measurement of one sensor consists of 40 measured values and these were measured at 20ms intervals, it often happens that the measured values differ greatly between two sampling times due to the rapid displacement of charge particles, which happens way faster than 20ms. This means that the value at the measuring point t has a high difference in the amount compared to the value at time $t + 1$, since the actual discharge event in between these recorded data points cannot be reconstructed due to the low sampling rate. This is the reason for using the maximum value difference of a measurement.

As we can see from the metrics of the different setups, the sensor setups vary in quality depending on which sensors are used because the location of the sensor is crucial. However, the values differ not only depending on which setup was selected, but also which classifier is used. Various classifiers of the WEKA framework were tested and evaluated. On average, classifier Naïve Bayes Multinomial was the best, but some classifiers were better at some setups than others. That is why in the following tests we use the Naïve Bayes Multinomial classifier to create confusion matrices for the conducted tests.

Since an important question of this evaluation is how many sensors are really needed to classify certain activities, all permutations of possible sensor placements were analysed. Different topologies are evaluated to test the placement and its effect in detecting different activities. The aim is to create the best possible, smaller setup and thereby gain knowledge about the necessity of sensors. A leave-one-out cross validation was used for each permutation of sensors. Hence, 14 of the 15 test runs were used as a training set and the remaining set was used for testing. This was done so that each record was used once as a test set. The results are the average results of the 15 runs. Naïve Bayes Multinomial was used as classifier because it supports multi classes as well as nominal and numerical attributes and it is known to generate good results [52].

Another relevant factor for this evaluation were the sensors itself, since the used sensors were hand-soldered and can therefore work variably well. The sensitivity of the sensors is also relevant. The ActiTag sensors can be triggered over a large distance, over 1.5m, as the data for the kitchen, living room and bed room shows. The amount of carried charge of the persons to be recorded also has significant impact. Therefore there are activities that generate fewer measured values because the threshold detector of the sensors are triggered less often because activities with smaller movements of the body in general generate less charge. For example, compared to the "Preparation" activity in the kitchen, the "Cookpan" and "Cookpot" activities generated very few measured values, which makes it difficult to detect them, especially if these measured values are similar to other activities. This can also be seen at the heat map for the kitchen activities, as shown in Figure 3.19.

First, the classifier is trained and tested with the data from all sensors. The following tables show the metrics and the confusion matrix for the classifier:

As we see, the classifier recognizes on average 55% of the data correctly. Among other

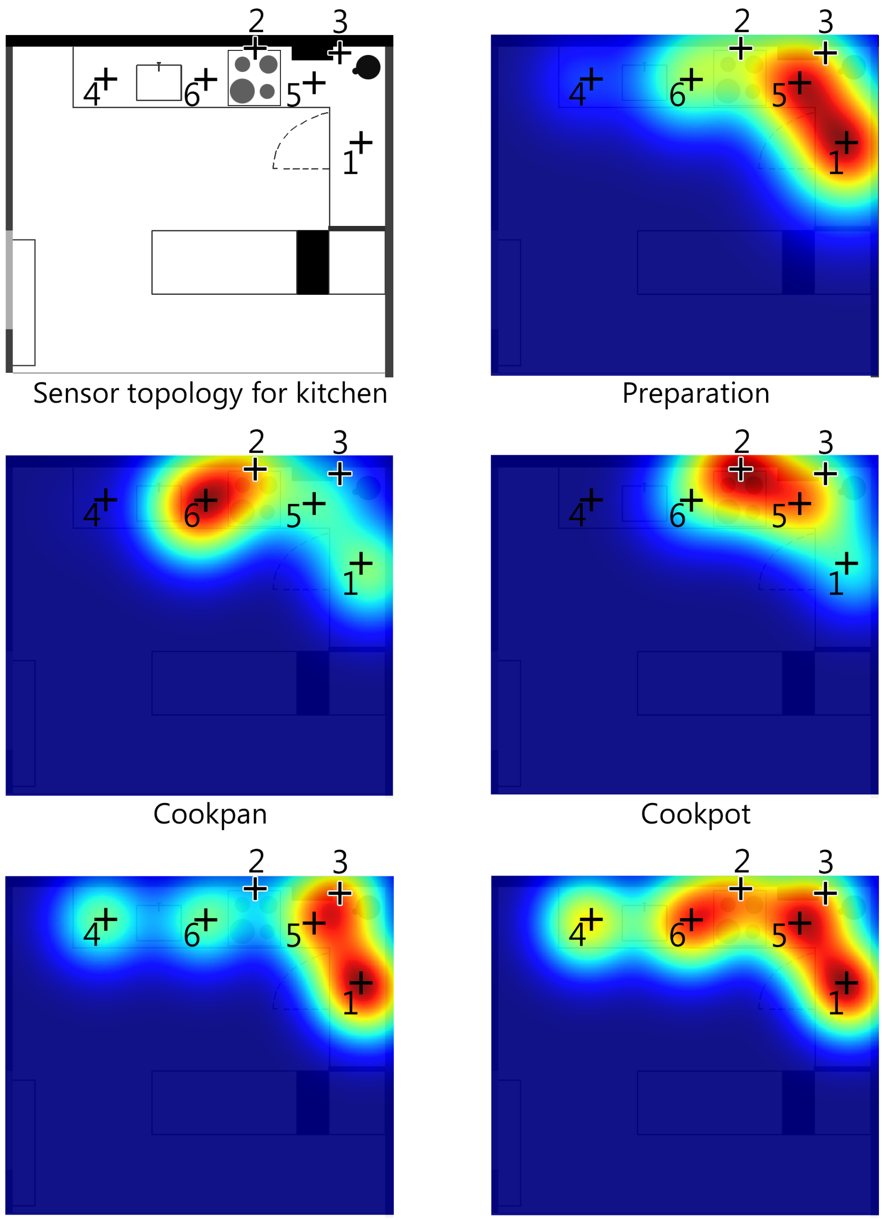


Figure 3.19.: Heat map displaying sensor participation for different kitchen activities.

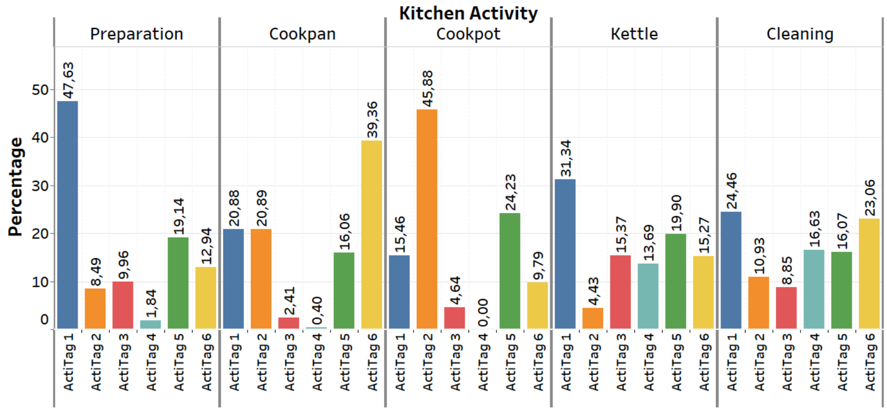


Figure 3.20.: Percental use of sensors for every activity in the kitchen

ActiTags: 1,2,3,4,5,6

Activity	Precision	Recall	F-Score	$F_{1-macro-avg}$	$F_{1-micro-avg}$
Preparation	0.6949	0.6941	0.6899	0.4719	0.5541
Cookpan	0.2456	0.5003	0.2922		
Cookpot	0.2713	0.6490	0.3514		
Kettle	0.4919	0.3497	0.3884		
Cleaning	0.6557	0.4825	0.5324		
weighted avg.	**0.6248**	**0.5577**	**0.5651**		

Table 3.6.: Scores for setup with ActiTags 1,2,3,4,5,6 for kitchen classification with NBM.

Confusion matrix setup 1,2,3,4,5,6

a	b	c	d	e	*Classified as*
113	12	18	8	13	**a= Preparation**
8	6	1	0	2	**b = Cookpan**
1	2	10	0	0	**c = Cookpot**
23	6	0	24	15	**d = Kettle**
22	12	11	17	57	**e = Cleaning**

Table 3.7.: Average confusion matrix for 1,2,3,4,5,6 for kitchen classification with NBM

ActiTags: 1,2,3,4,6					
Activity	**Precision**	**Recall**	**F-Score**	$F_{1-macro-avg}$	$F_{1-micro-avg}$
Preparation	0.6960	0.7071	0.6955	0.4750	0.5631
Cookpan	0.2815	0.5028	0.3265		
Cookpot	0.2629	0.7141	0.3425		
Kettle	0.4760	0.4044	0.4191		
Cleaning	0.6586	0.4641	0.5222		
weighted avg.	**0.6244**	**0.5674**	**0.5711**		

Table 3.8.: Scores for setup with ActiTags 1,2,3,4,6 for kitchen classification with NBM

Confusion matrix setup 1,2,3,4,6					
a	**b**	**c**	**d**	**e**	*Classified as*
93	10	12	8	9	**a= Preparation**
6	6	2	0	0	**b = Cookpan**
1	2	7	0	0	**c = Cookpot**
18	4	0	21	11	**d = Kettle**
18	10	9	16	47	**e = Cleaning**

Table 3.9.: Average confusion matrix for 1,2,3,4,6 for kitchen classification with NBM

things, the strength lies in the area of "Preparation" activity, which can be better recognized than others due to the localized exercise and the many training data and uniform sensors. The worst detection rates are found in the activity "Kettle". The confusion matrix shows that the activities "Preparation", "Kettle" and "Cleaning" are difficult to distinguish from each other. One reason for this is that there is a spatial separation between the activity hotspots sink and work surface in the "Kettle" activity. Therefore, the values at the sink can be confused with the activity "Cleaning". The activities of the sensors at the work surface result in the fact that the activity "Kettle" is not easily distinguishable with the activity "Preparation". The classifier also finds it difficult to differentiate between the activities at the stove, but the activities "Preparation" and "Cleaning" are also strongly represented in the misclassifications. Since the stove activities generated very little data, they are similar to the data from the other activities. This lack of differentiation between the activities is the reason why the metrics together with the F_1-scores are around 0.50.

After the classification of the full setup, smaller setups were examined. This experiment shows that it is not always beneficial to use all sensors available. For example, removing ActiTag 5 from the entire setup results in nearly the same values as the large, entire setup:

As the various evaluated sensor setups for the kitchen show us, it is important to place several sensors for such activities which are hard to distinguish. The setup consisting of ActiTags 1 (right worktop), 2 (above the stove), 4 (to the left of the sink) and 6 (between sink and stove) can even surpass setups with a larger number of sensors. This is because ActiTag 1 covers the main area for the preparation activity. Sensors 2 and 6 can distinguish the activities Cookpan and Cookpot at the stove, among other things with the support of ActiTag 1. However, it is noticeable there based on the detection rates that the activities do not trigger the threshold detection of the sensors frequently.

If the catchment areas of sensors overlap too much, one sensor is highly likely to provide the relevant data over the other sensor in its catchment area. This can also be observed in the kitchen on ActiTag 5 when comparing setup 1,2,3,4,5,6 (Table 3.6) and setup 1,2,3,4,6 (Table 3.8). The values of the metrics hardly differ from each other and are even higher in the setup without sensor 5.

The same patterns can also be seen in the living room. The main sensors for the TV remote activity is ActiTag 4, which is placed next to the TV. Sensor 5, which rests on the bookcase, is decisive for the book. A third sensor is required for a more precise distinction between the two sensors. ActiTag 6 is under the TV shelf on the floor and can be activated for both activities. This is also necessary to distinguish the way back to or from the sofa after the individual sofa activities. If the two activities in the data had been marked complete by hand after taking the objects, a distinction would also be possible without sensor 6.

The activities on the sofa can also be easily detected with less individual sensors. This can be seen in Figure 3.21 as well as in Figure 3.22. For a better coverage sensors 1 and 2 can be used. However, this again shows that additional sensors are not helpful in the case of overlaps of their detection area. With ActiTag 2 it is possible to recognize the “Legs Up” activity better, with ActiTag 1 the sitting down and standing up can be better recognized. The sensors can be used there depending on the desired accuracy.

The same pattern is repeated in the bed room. As apparent from Figure 3.23 and Figure 3.24, sensor 1 and 6 cover unique hotspots for activities, allowing good values for precision and recall to be achieved. The setups with only sensors 1,2,6 and 1,3,6 as well as their combination, setup 1,2,3,6, show that very good and consistent predictions can be achieved. However, the sensors apart from the main activities such as sensor 4 and sensor 5 do not contribute new information, hence these sensors are redundant.

3.3.6. Short Summary

In summary, it can be stated that the installation of sensors should be chosen in such a way that the main regions are sufficiently covered for the activities, depending on the type of sensor and its accuracy and sensitivity. Sensors that overlap are only necessary if the

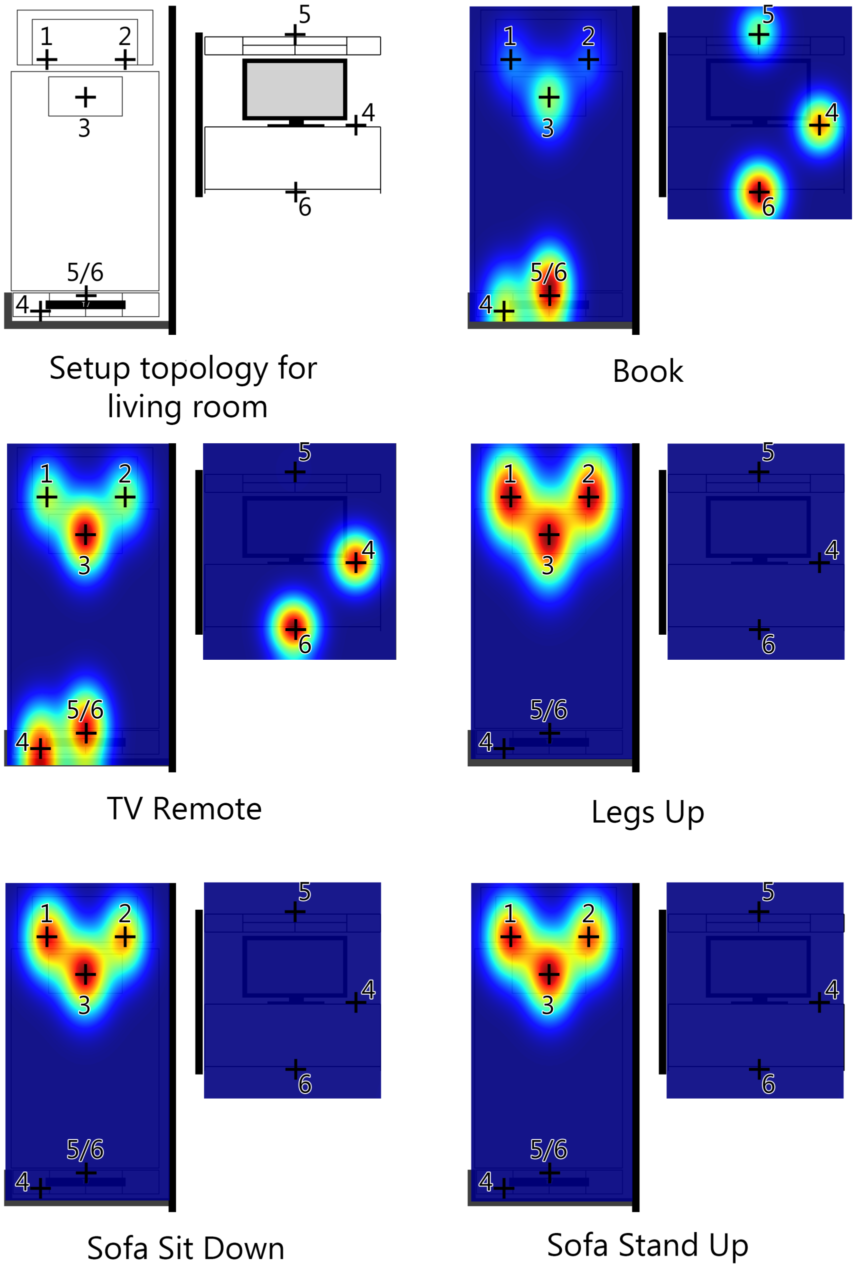


Figure 3.21.: Heat map displaying sensor participation for different living room activities.

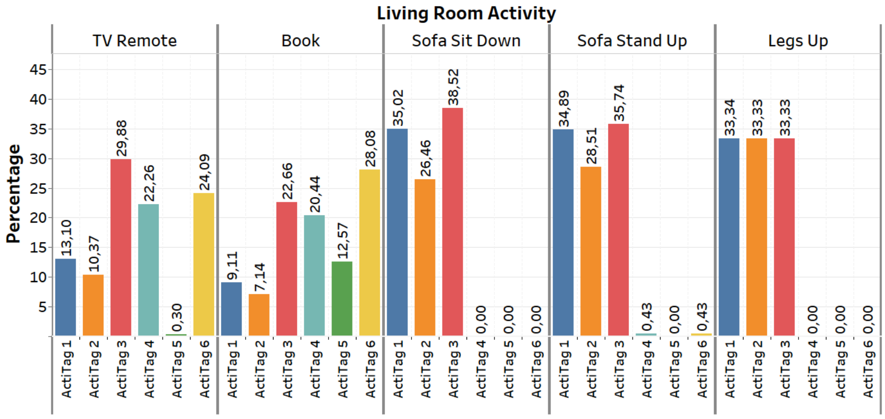


Figure 3.22.: Percental use of sensors for every activity in the living room

activities take place in a small space.

The data features used as well as the statistical classification approach are only suitable for classification to a limited extent, as evidenced by the data. Higher detection rates could be achieved by adding the shape of the time series instead of only looking at the number of deflections and the deflection height of the sensors or by using more advanced machine learning techniques. However, this investigation did not take place because the focus of the study is on comparing the number of sensors required.

The number of sensors needed depends on the action area that an activity covers as well as how extensive the movements of a person are while performing the activity. It was shown that smaller setups with less sensors can perform as good as setups with more sensors. But this is not generally the case.

3.4. Summary

The goal of this chapter is to answer RQ1:

Research Question 1 Can Passive Electric Field data be collected in a manner that improves usability and deployment cost?

In detail, the chapter explained how Passive Electric Field sensors can be designed and how to acquire data with them in a more cost effective and user friendly way. This also includes the number of sensors needed to record useful data.

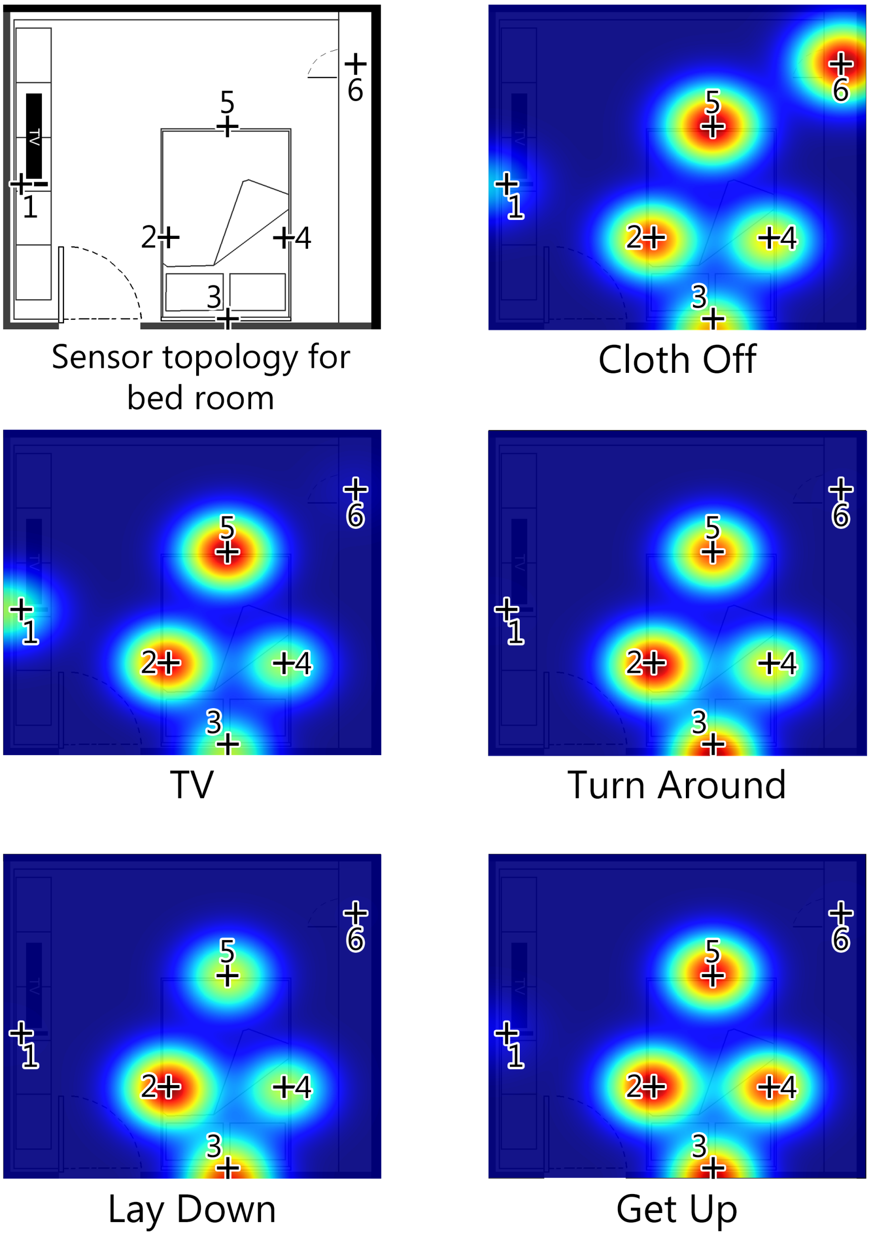


Figure 3.23.: Heat map displaying sensor participation for different bed room activities.

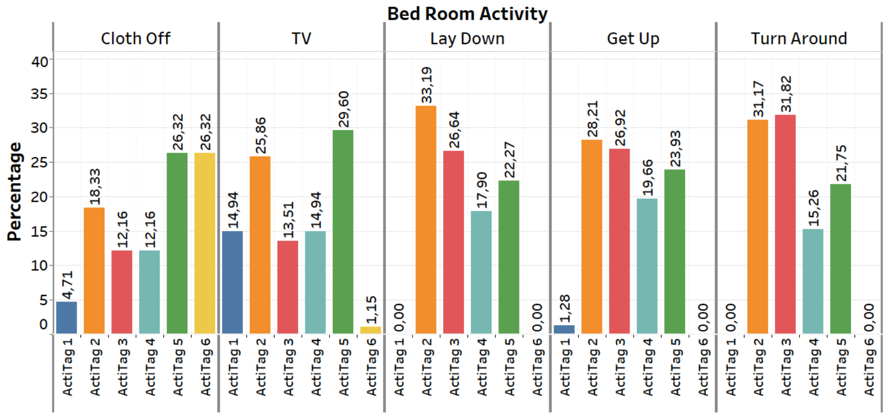


Figure 3.24.: Percental use of sensors for every activity in the bed room

In the first part of this chapter, a technique to eliminate the ground reference for Passive Electric Field sensors was introduced. The sensor design included a differential measurement approached, paired with a system to pre-charge both sensor electrodes to a certain voltage level. Using this design allowed for a more sensitive sensor on one hand, with a measurement range up to two meters, and on the other hand prevents the sensor of running into saturation problems for most signals.

After introducing the measurement technique, a toolkit was created to ease the use of these Passive Electric Field sensors. The toolkit focuses on usability and covering a wide variety of use-cases. Attention was paid to enable the user of the toolkit without constraining him in his choice of tools and experimental designs. To prove these statements, it was shown that experiments can be set up in a matter of minutes. In addition, a user study was conducted that questions the simplicity of the created toolkit. Nearly all users, experienced as well as inexperienced ones, agreed that the usability was very high.

In the last part of this chapter, the number of sensors needed to distinguish between certain activities of daily life was examined. It was shown that it is not always beneficial to use the maximum number of available sensors on hand. The results suggest that instead of collecting more data and putting the effort into data analysis, more attention should be paid to the actual physical placement of Passive Electric Field sensors. In areas with higher activities and more movement of the users, more sensors should be placed but only if there are several similar or related activities to differentiate.

All these techniques combined show that Passive Electric Field data can indeed be collected in such a manner, that the usability and the deployment cost likewise can be improved at the same time, hence answering Research Question 1. However, even though it has been shown that this technology can certainly be used to recognize and classify activities of daily living, it is not yet clear for which other use-cases Passive Electric Field Sensing can be considered. Because a use-case driven approach may be too specific, it is more beneficial to ask for the general area of application for these sensors, because different use-cases may benefit from different implementations.

That is why in the next chapter, a survey of application areas will elucidate the usage for Passive Electric Field Sensing further.

4. Application Areas of Electric Field Sensing Technologies

In the previous chapter, different optimizations for the deployment and usability of Passive Electric Field sensors were shown. For the investigation regarding the number of sensors needed, different activities of daily life were examined. However, because the range of applications for this technology is much wider, this use-case alone is not representative. It remains to be reviewed for which further application areas the technology can be used.

Hence, this chapter investigates a variety of different use-cases for Passive Electric Field Sensing answering RQ2 in the process:

Research Question 2 For which areas of application is Passive Electric Field Sensing feasible?

As already discussed, the technology is especially capable of sensing moving objects as well as other sources of moving charges, such as power transmission lines. It is necessary to discuss different use-cases in order to understand optimizations proposed for this technology, which will be done later on in Chapter 5.2.

As for the selection of use-cases, Passive Electric Field Sensing is applicable in much more scenarios than listed in this chapter. Because listing all possible cases where Passive Electric Field Sensing is feasible would exceed the scope of this thesis, this chapter presents a selected compilation of implementations for this technology. These selected use-cases were chosen in such a way that they shall cover important areas of daily life activities or examples that are directly applicable to those. Meaning that if all presented implementations would be used by a person that this person would interact nearly permanently with Passive Electric Field sensors.

That is why it was taken care of to select applications in such a manner to cover the daily routine of a person. At first, a person gets up and will have some sort of morning routine. Thus the first use-cases includes indoor applications, with the incorporation of objects and in passageways. After that, that person may leave their residence. Outdoors, a traffic related scenario was chosen. For situations were all of these sensors, indoors and outdoors, possibly are out of range, wearable applications that the user would always have attached to himself are demonstrated. This ensures that a person has many interactions with these sensors, regardless of what stage of the day they are in. All these use cases taken together therefore make it possible to assess how suitable Passive Electric Field Sensing is for everyday use. By spreading the applications as broadly as possible, as described above, a statistically relevant statement is to be generated in which application areas Passive Electric Field Sensing can be used (see RQ2). This approach was chosen because a provably complete enumeration of all application areas is impossible.

4.1. An Experimental Overview on Electric Field Sensing

This section is based on the previous publication [B.1.7] as well as the journal publication [B.2.1].

After introducing the basic working principle of Passive Electric Field Sensing in Section 2.3, we now come to the point, where we present some applications that are based on this sensor technology. We first reproduced a standard application of capacitive measurement: the recognition of presence. However, Passive Electric Field Sensing can be used for much more. Since we primarily recognize an activity, we try to use this fact to recognize from which direction a person approaches. To show that this is not only possible in controlled indoor environments, we also investigate the application outdoors in our third study. The recognition of the direction of motion thus leads us to a refined application for gesture recognition. This is shown in our fourth study. Finally, we demonstrate a further advantage over the plain old capacitive technology by the mobile application of Passive Electric Field Sensing.

4.1.1. Related Applications

Modern input modalities based on touch technologies, for example used in smartphones, tablets, elevators, and automotive interfaces tend to become increasingly intuitive to use. They want to empower the user to control these interfaces in the same way that a person interacts with another person or analog interfaces like sliders. Pointing, gestures, mimics, and movements are an important part of our language. This is why capacitive sensing has become a major input modality in the last years. Touch screens are optimal for small devices, since no big external devices like keyboards and mice are needed. But capacitive sensing has also found its way into the domain of ubiquitous interaction, where higher detection ranges are needed. Some capacitive sensors with many filtering and amplifying stages are able to detect objects at a range up to 200 cm [37]. Most of these systems generate an electric field on their own to sense their environment. Passive Electric Field Sensing in contrast, is able to achieve distances over two meters without any amplifiers. It can be implemented completely passive, meaning without generating an alternating current for field generation, because it picks up changes in ambient electric potential, generated by human movements. Because measurements with electric field sensing can be done through non-conductive materials, it is especially suited for ubiquitous interaction. The integration into the typical home environment is easy because it can be placed into furniture. The low power aspect of the technology on the other hand is a benefit for mobile usage.

A lot of our suroundings are composed of conductive materials. It's possible to turn most of these objects into smart objects by using the conductive parts as an input modality for capacitive sensing. Sato et *al.* published in their work Touché [63] different everyday objects equipped with interactive capabilities, like e.g., a smart doorknob to sense different grasp gestures and a smart desk to sense body gestures. Smart furniture, as shown by Kaila et *al.* [39] is also realized with embedded capacitive sensing techniques to make it smart enough to interact with users unobtrusively for smart home applications. It automatically fades into the background, if it is not used and offers visual input help as the user interacts with it. Braun et *al.* [5] worked on a smart wooden table called CapTap, which combines capacitive hand tracking and acoustic touch sensing. Similar smart furnitures like a capacitive sensing couch which is able to recognize your postures are proposed by Rus et *al.* [61]. Matthies et *al.* [47] have developed CapSoles which can identify 13 test participants based on gait analysis and classify the ground surfaces using machine learning techniques. Poupyrev et *al.* [55] even go a step further and turned flowers into electrodes to interact with the surroundings as introduced by the project called Botanicus Interacticus. However, these active capacitive techniques possess the same disadvantage in the sense of power consumption.

But capacitive techniques are not limited to static objects. Matthies et *al.* [48] use electrodes, which are placed in a person's ear, to classify facial expressions with electric field sensing.

The concept of Passive Electric Field Sensing has been explored more and more in recent years by various researchers. Cohn et *al.* [13] use the human body as receiving antenna and turn the electromagnetic noise which already exists in our environment into useful signals for home automation applications. His group further developed an ultra-low power wearable device to detect human body motion using static electric field sensing [12]. Another example for wearables based on electric field sensing that can detect movements of legs and even the touch of human hair is shown by Pouryazdan et *al.* [56]. Prance et *al.* [60] use electric field sensing to remotely detect heart rate signals (ECG). They are able to detect the electric field change almost 40 cm apart from the surface of the body. Große-Puppendahl et *al.* [26] deployed a prototype called Platypus using the Passive Electric Field Sensing to perform indoor localization and person identification. The most important advantage of these type of technologies lies is its low power consumption. Therefore, our research also relates to the field of Passive Electric Field Sensing. In this chapter, we present further explorative studies we performed to show the wide range of application possibilities using this technology.

4.1.2. Whiteboard Sensor

A limitation of Passive Electric Field Sensing is, as discussed in Section 2.3, that it is hard to detect non-moving entities. With classical capacitive sensing, this is not an issue. To show how it is possible with Passive Electric Field Sensing to detect static situations without any movements, we investigate a standard application for capacitive sensing - touch detection.

In this first experiment, we turned an unmodified whiteboard into an interactive touch sensor. Until now, the sensors used in other proposed experiments always filter out all frequencies above 50 Hz including the 50 Hz itself. In this experiment, an electric field sensor was modified such, that it filters out frequencies below 50 Hz. This is useful to overcome the constraint of the sensors that only movements can be detected. We especially deploy the 50 Hz component to detect the presence of a user. This experiment features a common whiteboard, which consists of at least one conductive layer. The surface of the whiteboard itself is non-conductive. For measuring the electric potential of the conductive layer, an electrode was attached on top of the non-conductive layer of the whiteboard. This means that the electrode has no direct contact with the conductive layer, but the electrode and the conductive layer are coupled in a capacitive way since they both resemble a small capacitor. Figure 4.1 shows the sensor as well as the attachment of the electrode.

As can be seen in Figure 4.2, a touch on the whiteboard caused by a user will result in an increase in the amplitude. This increased amplitude remains as long as the user touches the whiteboard. By constructing the envelope curve of the measurement, a simple touch sensor can be created. The sensor is able to deliver the information whether the whiteboard is touched.

This approach shows that electric field sensing is capable of substituting classical capacitive sensing in terms of touch detection. It also shows that electric field sensors can easily turn everyday objects into interactive entities. As long as the object features some conductive behavior, attaching sensors like the above can turn our surroundings into components of the Internet of Things. Especially in this context, low power consumption plays an important role.

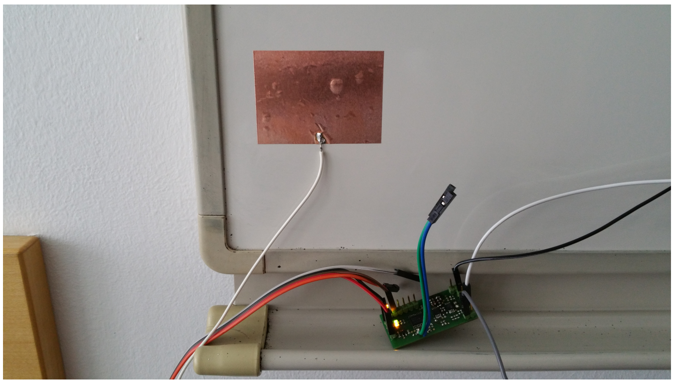


Figure 4.1.: Modified EF-sensor attached to a whiteboard.

4.1.3. Door Sensor

In our second scenario, the electrode of the electric field sensor was placed all around the door, in the form of a thin wire. The goal of this second experiment is not only the detection of persons in a room but also to detect if a moving person is entering or exiting the room. Because of the small diameter of the copper cable of the electrode that was used, the electrode was completely hidden within the rubber on the doorframe. The doorframe itself is made out of metal. This property is no requirement for the experiment but can be used to generate more information, as shown later on.

Figure 4.3 illustrates four simple classes that can be easily distinguished. As shown, the entry event of a person and the corresponding exit-event of the same person differ in magnitude. The reason for this is the location of the electrode. The electrode was placed on the outside of the doorframe, which consists of metal. The electrode was facing the inside of the room. The metal shielding of the doorframe reduces the amplitude of the measurement in the direction of the hallway.

Likewise, the amplitude of any activity inside the room can be detected better. That is the reason that the exit event of a person will always have a larger amplitude than entering the room. This holds only for the same person within a small time-frame, since the amount of charge of any entity, can vary over time, or even change its algebraic sign, which will then vary the amplitude of the signal accordingly. The closing and opening of a door can, in contrast to many other activities, be classified by the sign and form of the event recorded. Normally, the sign of the voltage amplitude of moving entities can change over time, as described in section 2.3. However, in the case of a installed door, the door is permanently connected to the ground potential and hence cannot build up

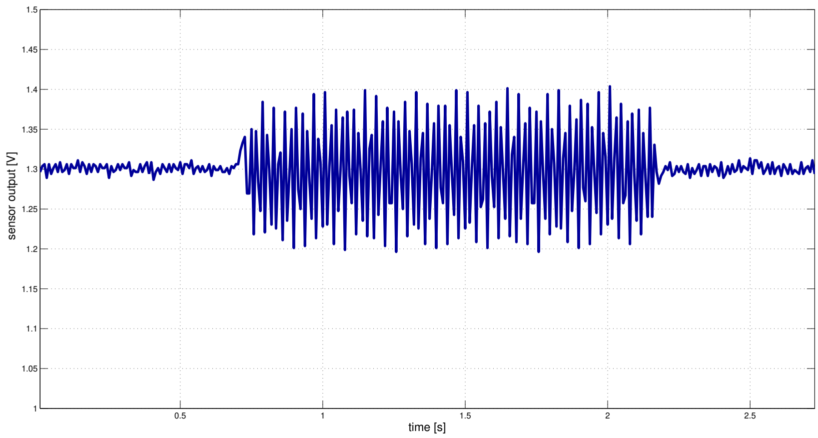


Figure 4.2.: Touch event on a whiteboard.

much static charge, except for small charges on the surface of the door. By closing the door, the ϵ (the electrical permittivity) of the virtual capacitor created by the electrode and the ground, changes. That influences its capacitance which results in a change of the measured voltage.

This experiment showed that it is possible to detect the direction of moving entities with a single electrode, even if only in a small timing window because of the described effects of fluctuating amounts of charges. To have a more reliable way to determine the direction, multiple electrodes should be used, as shown in a later experiment. In order to achieve the same functionality, the classical capacitive system needs larger transmitter electrodes and thus consumes way more power.

4.1.4. Traffic Observation

In the third application, the electric field sensor was deployed on the street, to test the sensor in a more open environment. This experimental setup should answer the question, if it is possible to distinguish between different participants of the traffic, like e.g., trucks, cars, bicycles or longboards. Since cars should influence the electric field significantly, electric field sensing could be an excellent technology for vehicle classification.

Figure 4.4 depicts the deployment of an electric field sensor on the street. Note that the deployment of the sensor did not take longer than a minute, this system is in particular suitable for fast and uncomplicated acquisition of traffic data. Vehicles and passengers

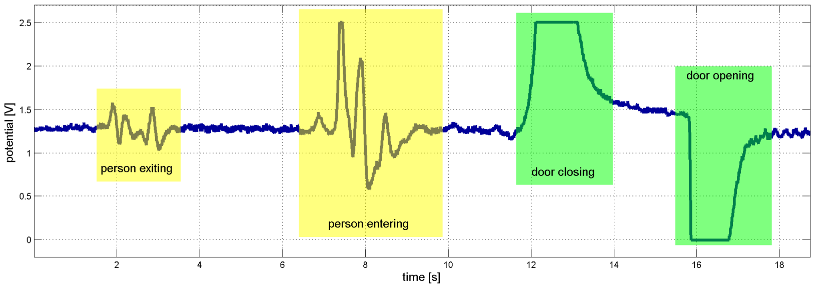


Figure 4.3.: Four different electrical footprints: a person exiting the room, a person entering, closing the door, and opening the door

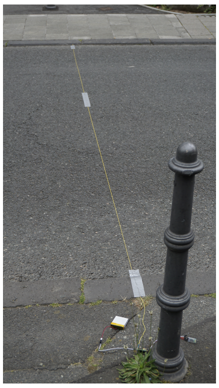


Figure 4.4.: Deployment of one electric field sensor on the street

are crossing the sensor deployed on the ground, and their electric footprint was collected. Since only one electrode was used, it does not matter in which direction the vehicles are moving.

Figure 4.5, Figure 4.6, and Figure 4.7 illustrate three different vehicles (a car, a truck and a bicycle) crossing the sensor electrode. The curves depict the electric footprint of the respective vehicles. The peaks are due to the wheels crossing the sensing electrode. Based on the spacing in time and the known distance of the wheels, we can further deduce the speed of the driving vehicles. The difference of the signal form and duration can be seen clearly. The peaks in signal were caused by the wheels crossing the sensing electrode. Therefore, if the distance of axes is given, by counting the time of two successive wheels generated a signal and the distance between the wheels, it is further possible to detect the velocity of the driving vehicle. A similar approach using the classical capacitive sensor

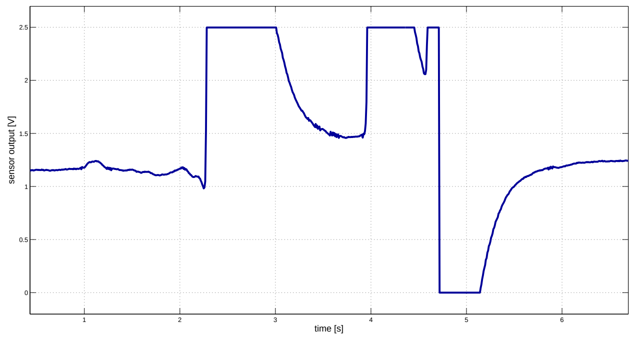


Figure 4.5.: Electric footprint of a truck

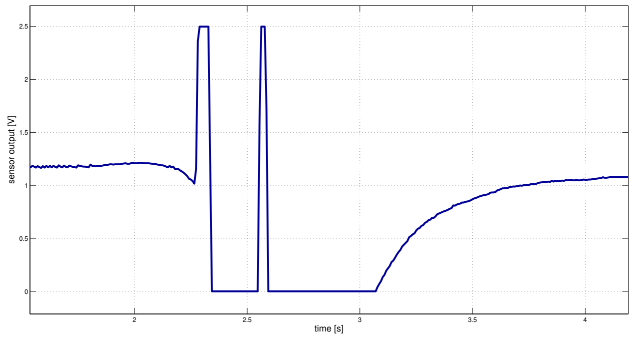


Figure 4.6.: Electric footprint of a car

should be investigated in the future.

4.1.5. Gesture Recognition

As a fourth use case, we show an example of refined classification of movement directions with multiple electrodes, as suggested in the second experiment. To demonstrate this, we propose a system for gesture recognition based on electric field sensing. We developed a prototype in the style of a smartwatch, called GeFish (Figure 4.8). The aim was to recognize gestures in a two-dimensional space. In order to measure the direction of a gesture, the electrodes are arranged symmetrically on four opposing edges of our "clock face". The direction of the movement can be calculated by considering the order in which

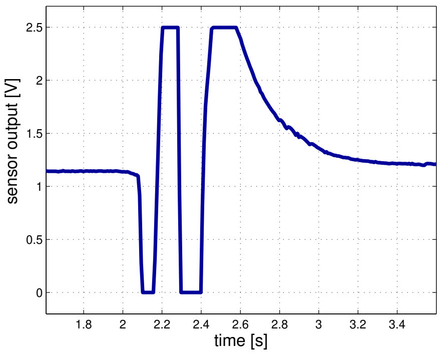


Figure 4.7.: Electric footprint of a bicycle

the electrodes were activated.

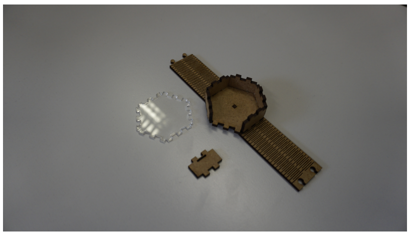


Figure 4.8.: The housing of GeFish.

For reasons of space and cost optimization, electrodes are built-in and are part of the PCB which is illustrated in Figure 4.9. Distinctive components are the operational amplifiers at the center, the big $1 \mathrm{G}\,\Omega$ resistors, and four electrodes. Every electrode is connected to two measurement groups. In comparison to the classical capacitive sensors, such small electrodes design would not be possible. The measuring distance would be too low for remote sensing. The signal without filters could be used to analyze the ambient 50 Hz field so that not only movements can be registered, but even the presence of body parts. The second measurement group only consists of a $1 \mathrm{G}\,\Omega$ resistor and an operation amplifier. An operational amplifier is used as a voltage follower, which is needed to increase the input resistance of the electrode. The resulting signal is fed into an additional ADC. If the signal were fed directly into the ADC, without using a voltage follower, the signal to noise ratio would be lowered because the input resistance of the ADC is not sufficient for the small currents induced by the user. At the bottom side of the board, the microcontroller and debug ports are placed (Figure 4.10).

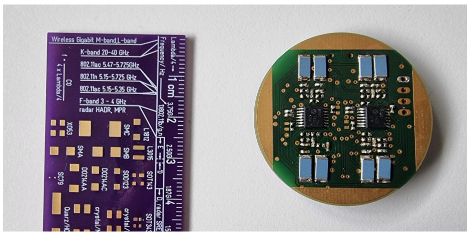


Figure 4.9.: GeFish top view.

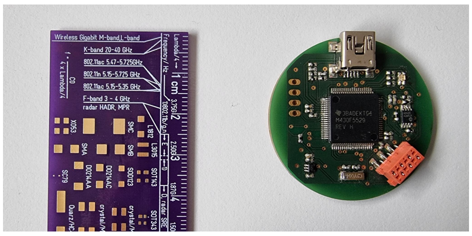


Figure 4.10.: GeFish bottom view.

The time difference between the signals of the four electrodes is used for determining the direction of movement. As depicted in Figure 4.11 a difference can be seen in the course of the four measurement curves. A simple state-machine is used to analytically find the typical pattern for a movement over a single electrode. This pattern is a sequence of a local extremum, followed by a zero-crossing, followed by another local extremum. After recognizing this pattern, the position of the zero-crossing is calculated. This procedure is done for every set of measurements of every electrode. A valid gesture in this context is if all four electrodes report an extremum-zero-extremum pattern within a certain amount of time. Another indicator is the relative time difference between those events. Absolute timing values will not do any good because every user executes gestures with different speeds. For this reason, a system was implemented which calculates the confidence of every direction and a confidence value for the situation that a gesture was done at all. So if the software is certain that the user has interacted with the system, it will output the direction, but only if a certain level of confidence is reached. That minimizes false positives since a user who walks past the sensor generates a similar pattern than a user making a gesture.

The functionality was shown in a small evaluation with 13 users. Each user performed a total of 12 valid gestures and 12 invalid actions. Some users had experience with touchless interaction, others did not.

	valid gesture recognized	no gesture recognized
valid gesture executed	126	30
invalid gesture executed	27	129

Table 4.1.: Evaluation data for gestures performed by GeFish

Table 4.1 shows the results of the evaluation. The recall of GeFish is 80.8%, and the precision is 82.4%. The overall accuracy is 81.7%. This experiment confirmed our thesis

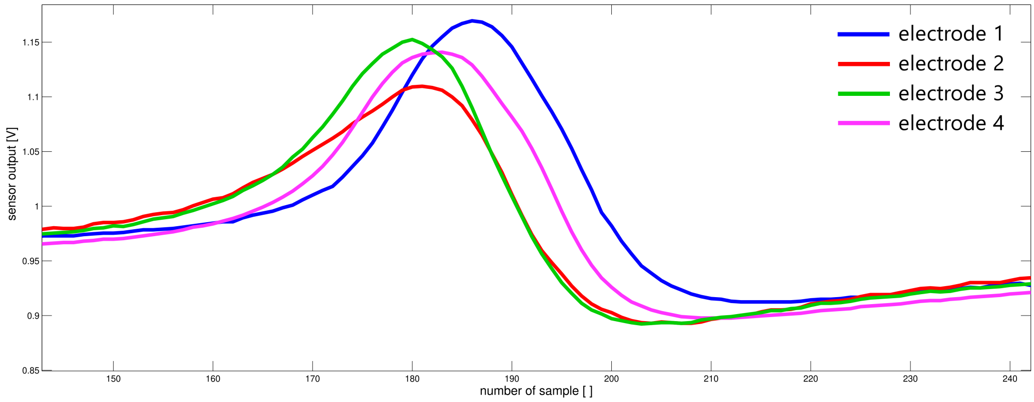


Figure 4.11.: A recording of all four electrodes of GeFish.

formulated in the second experiment, that it is possible to use electric field sensing for a robust detection of moving directions.

4.1.6. Wearables

In the previous experiments, the electrode of the sensors was always placed on a solid structure. That means that the potential to the ground of the electrode itself remained the same every time. The question arises what happens if the electrode is worn on the body so that the potential to the ground changes over time. The following experiment was conducted in cooperation with the University of Sussex. The electric potential sensor used in this experiment was designed by the University of Sussex [11, 21, 32] and further embedded into our custom-designed circuits. The used external sensor device is also known under the name electric potential integrated circuit (EPIC) and can be commercially purchased from the Plessey Semiconductors [1].

Figure 4.13 illustrates the sensor recording of approximately three minutes of activities. In this experiment, the person moving around is equipped with a variety of different sensors (see Figure 4.12). Accelerometers and gyroscopes are embedded in each shoe to serve as a reference to our electric field measurement. This reference sensor system embedded in the shoes was also in courtesy from the Sensor Technology Research Centre of the University of Sussex. Four electric field sensors are worn directly on the skin; two sensors are deployed on the shoulder, one on the back and one on the hip. All sensor are

[1] http://www.plesseysemiconductors.com/

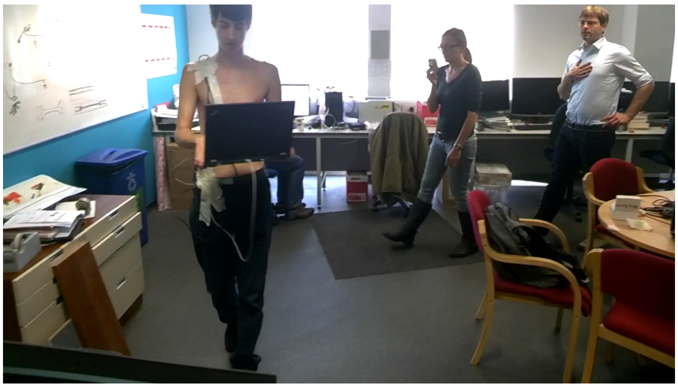


Figure 4.12.: A person wearing multiple Passive Electric Field sensors on the right shoulder, the hip and their back.

directly connected to the skin. The last row of Figure 4.13 represents the average of these four Passive Electric Field sensors. Additionally, all activities were recorded on video. A synchronization procedure is used to match the timing of the sensor readings to the video.

From second 20 to second 75, the person is walking around. Then the person stood still for a couple of seconds before walking to a table afterward. At 90 seconds, the person takes a seat and starts typing on a keyboard. The signal at each time, when the person is in motion can clearly be seen in the recording from Figure 4.13.

Figure 4.14 illustrates the sensor readings while walking over a pad of rubber. As seen in the recording, a natural step results in a pattern with two bulges. The pattern arises from the typical movement of a foot while rolling off the floor. When walking over a different type of floor, like a pad of rubber, a change of amplitude in the recording can be noticed. Exactly three steps were made on the rubber pad as marked in yellow in the measurement, where three step-pattern have got a smaller amplitude. This implies that electric field sensors, when worn on the body, can provide information not only for the activities of a person but for the environment itself.

Another example for monitoring external influences can be seen around second 150 in Figure 4.13. At this point, the person wearing electric field sensors was touched by another person, resulting in a big change of amplitude. Again, the problem of ambiguity occurs. By looking at all available contextual information, it is easy to come to the conclusion that an external influence caused the distortion since all other accelerations and gyroscopic sensors have no deflections. However, to spot the reasons of the distortion at second 150, there is not enough data just by looking at all sensor graphs without further knowledge. To identify the source of such external influences, a bigger sensor array of electric field

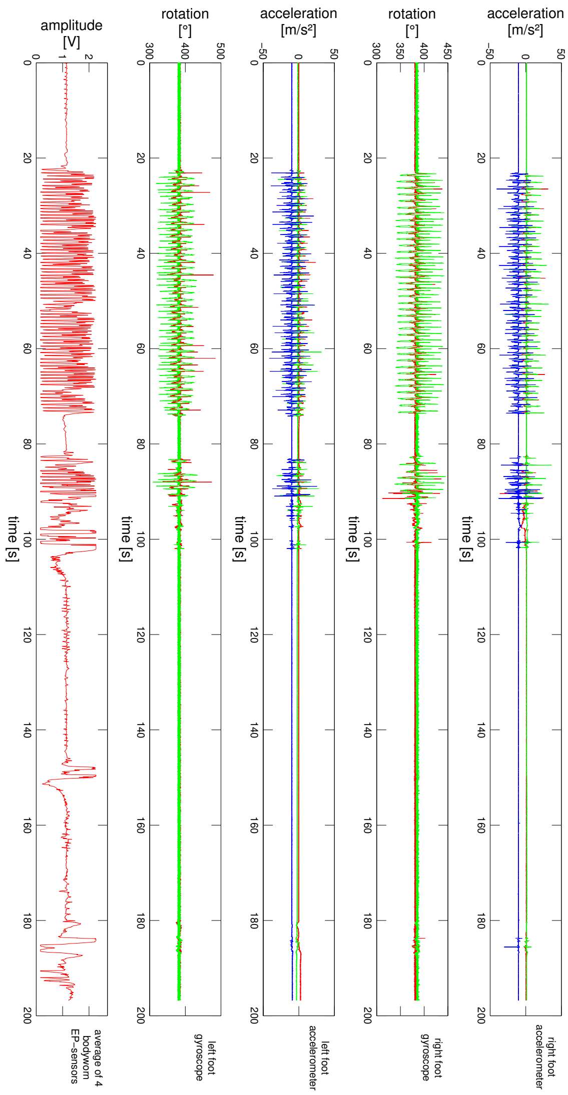


Figure 4.13.: 3 minutes walking and typing.

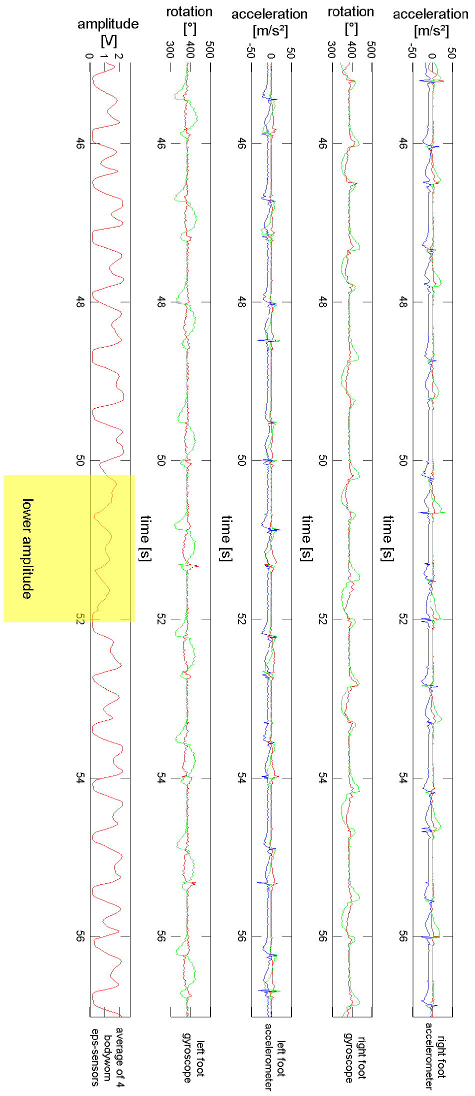


Figure 4.14.: Walking over a pad of rubber.

sensors is needed than in this recording.

Surprisingly, even without a big array of sensors, very small movements and activities like typing on a keyboard can easily be spotted. Figure 4.13 focuses on the activities at second 120. The person wearing the sensors is sitting still, which can be deduced from the acceleration sensors. With acceleration and gyroscopic sensors only, it is impossible to spot such small movements if the sensors are not worn directly on the fingers or near the fingers. However, even without wearing an electric field sensor on the arms, typing on a keyboard produces a unique pattern in the recording.

The experiment showed that electric field sensing in mobile applications can generate a lot more information than currently used technologies such as accelerometers while being very energy efficient. We have shown how sensitive this measurement method can be. This application opens up a wide range of possible applications in the areas of sports and fitness, as well as in health care.

4.1.7. Limitations

During our experiments, we also learned some limitations of the electrical field sensing technology. In this section, we will give a brief overview of physical limitations.

To conclude all experiments, we collected all use-cases introduced in this work so far and put them into Table 4.2 for a better overview of the advantages and disadvantages of the electric field sensing system.

A disadvantage over the classical capacitive measurement is the inability to detect objects, which are tied to the ground by an electrical connection with a small resistance. As we learned in section 2.3, we measure the voltage U which is a function of the charge Q and the capacitance C. If an object is tied to ground, its charge is zero and will remain zero since every charge of the object gets instantly drained off. This means that no detection of a grounded object can be accomplished.

Similarly, if the object of interest is positioned behind a grounded object, it is very hard or not possible to detect. A scenario for this constellation to happen could be when trying to use this technology to create a smart floor; A person is standing in the bathroom with the floor covered by water. Even if the person is wearing non-conductive shoes, and thus has no connection to ground, it would be impossible to detect the person with sensors underneath the floor. If the water is grounded, the capacitive coupling between the person and the electrode of the sensor is effectively eliminated.

Strong electrical fields also represent a difficulty for a clean measurement. Just by placing an electrical field sensor near a power outlet can result in a lot of interference. This problem can be overcome with analog filters, but this approach either increases the overall power consumption of a sensor, or weakens the signal amplitude.

4.2. Improving Presence Detection

This section is based on the previous publication [B.1.2].

In modern smart spaces, the information of the presence of users is mandatory for many systems. By knowing the number of users in a room, smart devices can adapt their behaviour to fit the current situation. For example, lights can be turned off in case no persons are present to save energy or music speakers can increase the volume when more persons enter the room.

Commonly used presence detectors that are based on infrared detection are not sufficient for this application. If a person enters a room and remains calm, a simple infrared based sensor has no means to know if the person left the room or is sitting nearly motionless in the room since they are designed to function as a switch.

There are a variety of other sensor types for presence detection. Optical barriers can improve this situation, but do not cover other aspects of real life situations. If two light barriers are placed at every entrance of a room, directional information of exit- and enter-events can be calculated. However, optical systems lack the capability of differentiating between objects and persons.

To improve this situation, a directional sensor (shown in Figure 4.15) based on Passive Electric Field Sensing has been implemented. As shown later on, these sensors react very sensitive to steps, but insensitive to objects with wheels. They will not be recognized by the detection algorithm. In addition, compared to mere active capacitive sensors, the Passive Electric Field Sensors have a higher detection range, making them more suitable in wider door frames than their active counter parts.

The principle of electric field sensing is well known for over hundred years, but lots of application areas have been revived in the last few decades with emerging new processing algorithms and sensor designs. This technology gained lots of popularity in sense of low power consumption, no emission of electrical fields and high privacy preserving aspects. In the medical domain, applications like remote EEG measurement has been implemented by Prance et *al.* [60]. In the previous section, a lot of exploratory experiments for different use cases were shown, for example no-touch gesture recognition for wearables and traffic observation using electrical field sensing [80]. Große-Puppendahl et *al.* [26] worked with the possibility of using this technology for indoor positioning and even person recognition based on gait patterns on two different days. Similar work for indoor positioning system using electrical potential sensing on a smart floor has been presented by Fu et *al.* [19]. Cohn et *al.* [12] made some efforts by applying this technology in gaming context. They augmented a customized gaming pad into a device with multiple input modalities like jumping and stepping without using the control stick on the gaming pad. Examples of wearables based on electric field sensing that can detect movements of legs and even the

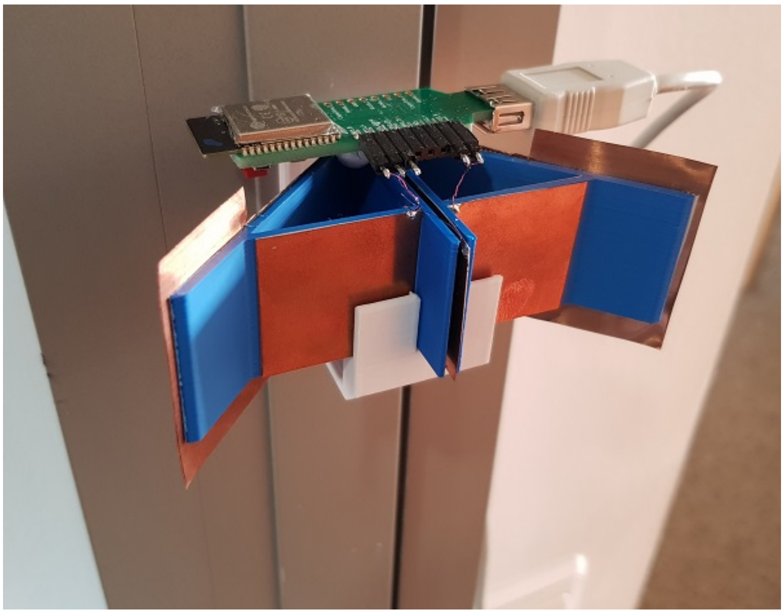


Figure 4.15.: sensor and copper electrodes placed on door

touch of human hair is shown by Pouryazdan et *al*. [56].

A door as an entry point to a secured location is quite interesting to interact with. Gjoreski et *al*. [22] showed in their work that it is possible to identify person by just analyzing door accelerations in time and frequency domain. In the following sections, we present a novel use-case of electrical potential sensing to be a smart presence detector. We first introduce the hardware implementation, followed by the detection algorithm and finally conclude our findings in the evaluation section.

4.2.1. Hardware Implementation

The sensor contains four core components. These components are:

- A UART to USB bridge for communication purposes
- An ESP32 micro controller of which two ADCs are used in 12bit mode
- Two Passive Electric Field Sensing groups
- Two shielded electrodes for every sensing group

A measurement group consists of an instrumentation amplifier, which meters the voltage between two pre-charged electrodes. To pre-charge the electrodes, half of the supply voltage is linked to both electrodes over two $1\text{G}\Omega$ resistors. The current running through these resistors slowly pulls the measured signal back to a defined voltage level, removing some of the wanted signal in the process. To prevent a too strong loss of the signal, these resistors have to have a high value. Omitting these resistors would result in a higher range and increased sensitivity of the sensor, but would also introduce the problem of railing voltages. This happens if a voltage over the supply voltage (3.3V) or a negative voltage is created between the electrodes. Without pre-charging of the electrodes, the voltage level would not (or very slowly) recover to a range measurable by the ADC of the micro controller. By tying the potential of the electrodes to 1.65V, the sensor values will normalize within seconds, even if railing occurred. Figure 4.16 shows the simplified circuit of a measurement group. If the voltage of the first electrode is p_a and the voltage of the second electrode is p_b, the voltage u given by the instrumentation amplifier will be:

$$u = \frac{1}{2}V_{cc} + (p_a - p_b)$$

The voltage u is sampled by an ADC of the micro controller and further processed. This voltage is influenced by movements of the human body. Since there is a tiny amount of charge on the body, it will attract the opposite charge on the electrodes while approaching the sensor, but not the same amount on every electrode because of the arrangement of the electrodes. The induced potential difference between both electrodes is the input for our instrumentation amplifier.

4.2.2. Detection Algorithm

Since the sensor consists of two measurement modules, every module will output its own measurements. The measurement modules use a scan frequency of 50 Hz, the frequency of the European power grid. In this way, noise created by power outlets and power lines is suppressed by under-sampling. A more detailed explanation of this under-sampling technique is given in Section 5.1.

The two outputs of the sensor will be processed by a pipeline. Every module uses a 12 bit ADC, which is equal to values from 0 (= 0V) to 4095 (= 3.3V). Because of the pre-charging of the electrodes, the normal baseline of a module is 2048, around half of the measurement range. Due to variances of the electrical components and environmental conditions like air humidity and temperature, the baseline can have an offset up to 10%, as indicated in the data sheet of the components used, of the original 2048. This is why the first stage of the pipeline is to calculate the real baseline of every measurement module

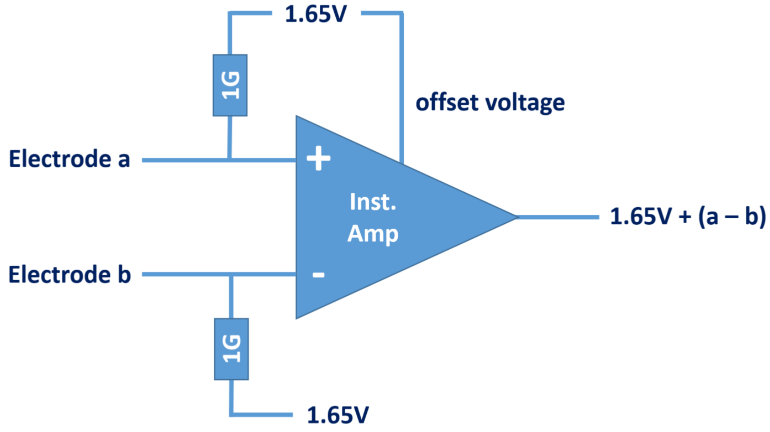


Figure 4.16.: simplified circuit of a measurement group

and subtract it so that the values are zero based. This stage will only be active if there were no activities for at least 25ms. Otherwise the sensor would calibrate its baseline to the level of human steps.

The second stage is to form the first derivative of the two signals. This is needed to calculate the moment when the feet of a person hit the ground, which is represented by a local minimum or maximum. Note that no information can be obtained by the distinction of minima and maxima, because this only depends on the charge of a person. If a person is charged negatively, their steps will give a negative amplitude, otherwise a positive. The position of the extremum will be stored, but only if the following conditions are met:

- The first derivative is crossing the zero line. The direction of the crossing does not matter out of the stated reasons.
- The amplitude of the signal has to overcome a certain threshold. Simple noise will be discarded this way.
- The extremum has a certain minimal euclidean distance to the previous extremum. This way, if a single extremum that was corrupted by noise would appear as two or more extrema, the algorithm will only note one extremum.

This stage only operates on the previously calculated positions of the extrema. If no new peaks are detected for at least 25ms, the third stage of the pipeline is processed. For each peak we compute the sign of the difference in amplitude of the two signals. The electrodes of the sensor are placed in such a way that the position of a person in relation to the sensor will give a stronger signal in one measurement module, depending on if the person is moving on the right of the sensor or on the left. When calculated for each peak, this stage of the pipeline will result in a sequence of negative or positive peaks. In a best case scenario, a person which is moving from right to left would give the sequence: +1, +1, ..., +1, -1, -1, ..., -1. Note that the number of peaks is determined by the number of steps of the detected person.

The fourth and last stage of the algorithm is an auto correlation. Four different cases of sequences are evaluated:

- $\{+1, +1, ..., +1, -1, -1, ..., -1\}$: The person is moving from right to left
- $\{-1, -1, ..., -1, +1, +1, ..., +1\}$: The person is moving from left to right
- $\{+1, +1, ..., +1\}$: The person is moving only on the right side of the sensor
- $\{-1, -1, ..., -1\}$: The person is moving on the left side of the sensor

These are ideal sequences. A normal given sequence could contain outliers that obfuscate the sequence. To eliminate those, every +1 or -1 that has no adjacent peak with the same sign will be discarded. For example, the sequence $\{+1, +1, +1, -1, +1, -1, -1\}$ would result in $\{+1, +1, +1, -1, -1\}$. The auto correlation is only computed if three or more peaks are contained in the reduced sequence. Otherwise the result will be unreliable. Such weak signals are discarded because they originate most likely of persons moving at a large distance of the sensor or noise. In these cases, the algorithm will output the none-class. If there are enough peaks, the auto correlation matches the reduced sequence with these four functions:

- person moving left to right: modified Heaviside step function

$$H_1(x) = \begin{cases} -1 & x \leq 0 \\ 1 & x > 0 \end{cases}$$

- person moving right to left: inverted modified Heaviside step function

$$H_2(x) = \begin{cases} 1 & x \leq 0 \\ -1 & x > 0 \end{cases}$$

- person moving on the right: constant positive function

$$P(x) = 1$$

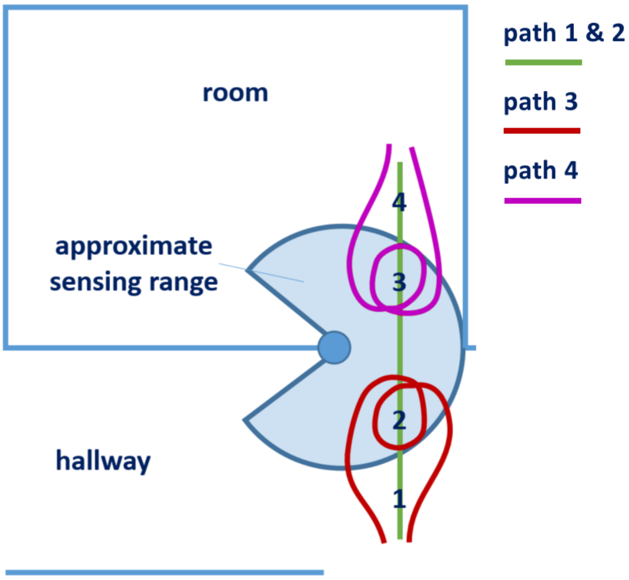


Figure 4.17.: evaluation setup and walking paths

- person moving on the left: constant negative function

$$N(x) = -1$$

The function with the lowest error will be selected and represents the final result of the algorithm.

4.2.3. Evaluation

To illustrate the proof of concept, we conducted a test study with 12 participants. The participants have an average height of 174.9 cm ranging from 163 to 186 cm and contain 5 females and 7 males. We asked the participant to walk on predefined paths as shown in Figure 4.17. Each path were taken twice to determine the 5 different target classes of {*inside* (path 4), *outside* (path 3), *exit* (path 2), *entry* (path 1), *none*}. The approximate sensing range is indicated by the area of the blue circle. Four positions from 1 to 4 have been marked to indicate the path. The walking speed is not constrained. The walking direction was instructed as given in Table 4.3.

We noted the success- and mismatch-rate for each run to derive the confusion matrix shown in Figure 4.18.

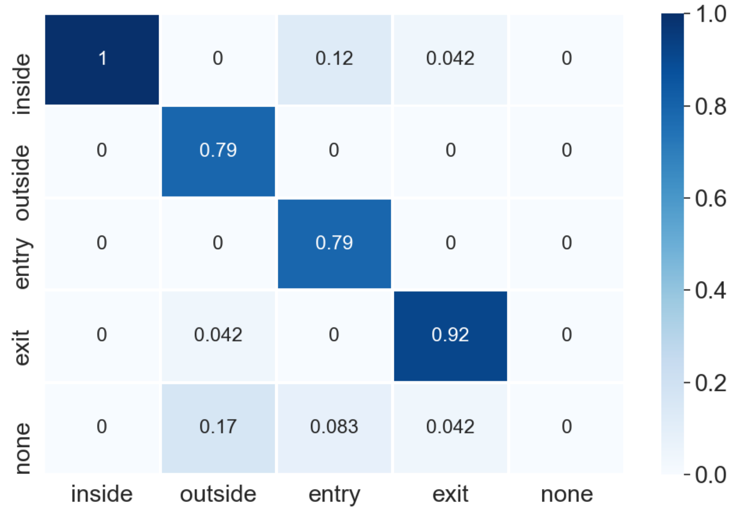


Figure 4.18.: confusion matrix of the five different classes

We did an additional experiment to show that electric field sensing in contrast to photoelectric sensors will not be disturbed by objects. In Figure 4.19, we plotted two different signals. The upper plot shows the signal, when a person is entering the room rolling a wheel chair, while the plot below shows the signal when a person is entering the room without any objects. As shown, the signals are nearly identical and do not contain any features indicating another moving object. Both entry events were classified correctly by the sensor. This shows that rolling objects do not disturb the sensor.

4.3. Conclusion

In this chapter, we compared capacitive sensing to Passive Electric Field Sensing and discussed various use-cases for this technology to answer RQ2:

Research Question 2 For which areas of application is Passive Electric Field Sensing feasible?

Not only did we describe possible areas of application, with our data we are able to prove that this technology is really potent and that in some scenarios it would be beneficial to use electric field sensing instead of currently established technologies, for example loading mode sensors and accelerometers, as shown by our experiments. That is because

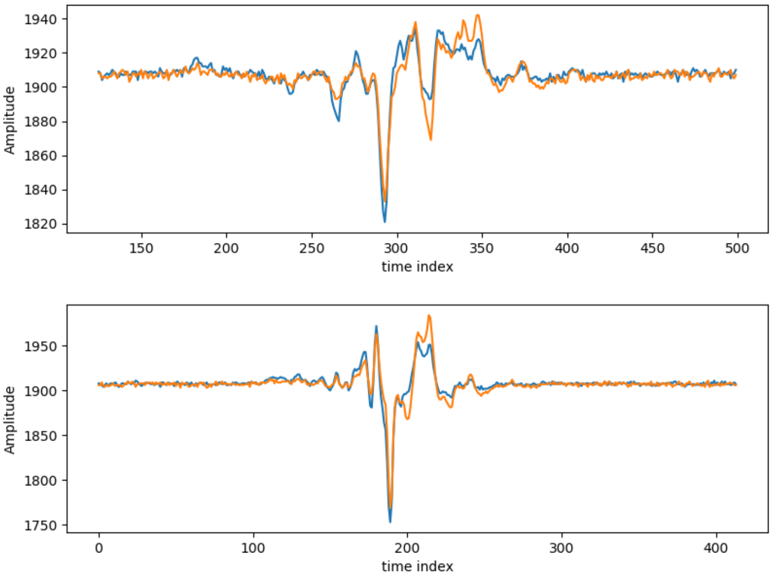


Figure 4.19.: signal of entering the room with (above) and without (below) wheelchair

in the cases presented in this section we can generate a lot more information with electric field sensing without the need of fusing several sensor technologies. In the five use cases, we have shown that the presence and activity of persons and machines are recognized. The direction of activity can also be determined. Thus, gesture detection is also easy to implement even with a small electrode surface. We also showed the advantage of the mobile application.

Since we only presented a small compilation of conceivable use-cases, there is a lot of other applications that should be explored with this sensing technology. Future work with electric field sensing could involve a variety of new uses. For example, the detection of water damage in large structures, since it is a technology that is can be realized with very view components and hence can be easily integrated, with the possibility of large and flexible layouts for electrodes, or new devices for x-ray like machine-vision in non-harmful ways by creating large electric field sensor arrays. Alternatively, high-resolution localization of charged entities with only very few sensors based on the "time of flight" of charge redistribution, which would require more sophisticated setups and signal processing. There are still a lot of scenarios worthwhile exploring.

We also presented a novel approach for counting exit- and entry-events with a sensor based on electric field sensing. The evaluation shows that this concept is promising.

To improve the performance even more, the placement of the sensor could be further examined and optimized. An important point would be to enhance the implementation to detect multi-user scenarios. Regarding the advantages of this technology like low power consumption, no need for direct line of sight and insensitivity to objects, this technology is very suitable for this use-case.

While outlining the feasible application areas for Passive Electric Field Sensing in this chapter, the signal processing of the acquired data as well as the hardware setup were included to a certain extend, but this chapter did not elaborate these topics. To conclude and better understand what information can be harvested from Passive Electric Field data, the next chapter will discuss which general signal processing techniques are suitable for this. In addition to discussing more software related optimizations, it will be shown how certain hardware aspects of this technology can be optimized.

Use Cases	Advantage	Disadvantage
Whiteboard sensor	simple to install	50Hz ambient field needed
	bigger sensing areas possible than with loading mode sensors	applicable indoors only
Door sensor	small electrode size possible	not applicable for conductive (steel) doors with grounded frame
	can be retrofitted to existing doors	absolute amplitudes are only comparable for a short time
Traffic observation	fast deployment	weaker signal on wet streets
	can also be used for smaller vehicles like bicycles	axis distance or multiple sensors needed for speed determination
Gesture sensor	low energy consumption suited for mobile applications	cannot detect static gestures
	easy gesture processing	only implemented for 2D gestures
Wearables	more accurate readings than other sensors	needs to be close to skin
	many application areas	Data can be ambiguous

Table 4.2.: List of introduced use cases presented in the paper realized with electric field sensing compared to same technologies built in case using capacitive sensing.

Entry	Straight line from Position 1 to Position 4
Exit	Straight line from Position 4 to Position 1
Outside	Starting from Position 1 to circle around Position 2 and return back to Position 1
Inside	Starting from Position 4 to circle around Position 3 and return back to Position 4

Table 4.3.: The selection of pre-marked paths regarding the different classes has been given and each path was taken twice.

5. Optimizations for Passive Electric Field Sensing

This chapter is based on the journal publication [B.2.4].

As depicted in the preceding chapter, Passive Electric Field Sensing can be utilized in a wide variety of application areas, but also bears certain limitations. To better understand how one could implement countervailing measures to these limitations, the focus of this chapter is to answer RQ3:

Research Question 3 How can the use of Passive Electric Field Sensing be optimized?

Since the focus of the preceding chapter was laid onto the application areas of Passive Electric Field Sensing, the hardware setups and signal processing for these were briefly discussed, but not enough to understand which parameters could have been altered instead of the presented ones. Thus, a discussion of how to optimize Passive Electric Field Sensing is necessary to address these shortcomings of the previous chapter.

There are different approaches to optimize Passive Electric Field measurements. First of all, it should be clarified that optimization in this context can imply several things. The most important aspect is to enhance the signal to noise ratio of a sensor, which can increase the measurement range of a sensor as well as the sensitivity. Other aspects that can be improved are the reliability and validity of a sensor, since these do not increase when enhancing the SNR.

Because there are, to the best of my knowledge, no other explicit development kits available that offer Passive Electric Field Sensing functionality, all considerations in this chapter will be mainly done with the Linoc toolkit in mind, as presented in Chapter 3.2. But many of these considerations are transferable to other sensors, especially Passive Electric Field sensors, since these considerations represent the implementation of common techniques for Passive Electric Field sensors, because they already are used in similar forms today in different fields of applications. For this reason, it does not affect the validity of the suggestions presented if the following optimizations are based on a specific sensor toolkit.

5.1. Signal Processing

As described in Section 4.2.2, local extrema detection is an important method for extracting information from electric field data whose baseline is generated using hardware components, such as high-impedance resistors for slow pre-charging of electrodes. For systems which are lacking this kind of baseline generation, peak detection can be much more challenging because these sensors are reaching their saturation limits before an action is recorded completely. Even in systems with built-in hardware baseline compensation, this type of problem can occur, as shown in section 4.1.4, when trying to capture events from fast-moving objects that may carry a large amount of charge.

Even if an event does not saturate the used sensor, and even if the electronically generated baseline for this signal would be a precise predefined value, the absolute level of the recorded sensor signal most likely does not transport any information. That is because the amount of charge on an objects changes over time. For example, if two simple step patterns were recorded of a person that walks by an passive electric field sensor, the absolute level of the sensor amplitude can differ beyond the sensors noise. The more time lies between those two recordings, the bigger is the potential amplitude difference. As a matter of fact, not only can the amount of charge on an object change, the algebraic sign of the amount of charge can change as well, causing the recorded sensor signal to appear to flip around the time axis.

That leaves the question if the amplitude of an electric field sensor is even able to contribute information to any use-case. A circumstance that can be exploited to still gain information is, in many use-cases, that the amount of charge changes only slowly over time. Note that in this general discussion, it is not possible to clearly quantify the term "slowly" more exactly since it is dependent on the use-case of the technology. In a bathroom scenario for example, by touching grounded faucets or valves, the user nearly instantly discharges. A real life recording for this kind of event can be seen in Figure 5.1.

The picture illustrates a discharge event of a person by touching an electrical ground while being near a sensor, recorded with an passive electric field sensor configured with a 50 Hz sampling rate. It can be observed that this discharge event is shorter than the 20ms resolution of the used sensor and that the sensor needs approximately 150ms to re-calibrate itself until it reaches its normal baseline again.

The described scenario and the recorded data show that comparing absolute voltage levels is not applicable if the use-case is prone to rapid charge- and discharge events. But in scenarios where this isn't the case, a comparison between sensor amplitudes can make sense. An example use-case was already given in Section 4.2. Here, amplitudes are compared in the event of a person entering or exiting through a door. While entering or exiting, there are no opportunities for an occurring discharge event, since possible

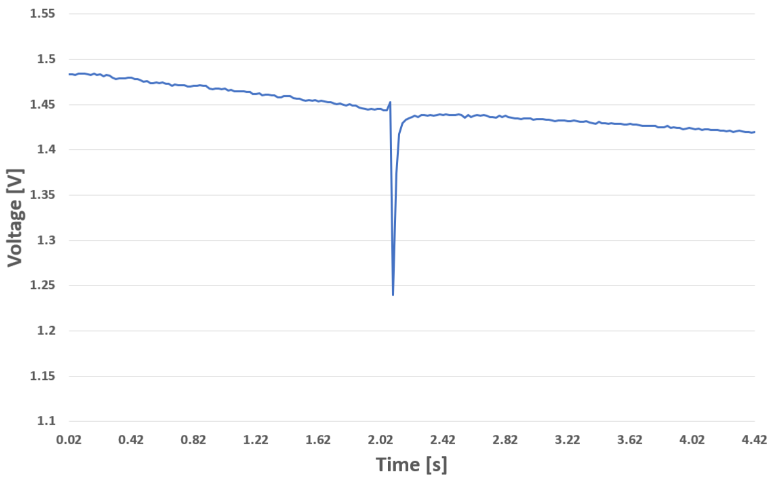


Figure 5.1.: Discharge event

discharge events like touching the door handle would occur before entering or exiting. Even if the person in question would wear no shoes or shoes that grant an ohmic connection to ground, this statement holds true since the discharge would take place before reaching the door. Further more, the time span of traversing a door frame is short so that the charge gained via the triboelectric effect during this event concerning the shoes of a person is negligible.

In summary, the following recommendations should be followed to extract the most information from the absolute level of accumulated charge:

- The use-case in question should pose no opportunities for the measurement target to gain or loose large amounts of charge.
- The algebraic sign of the charge has to be ignored, but could be of use when comparing short periods of the same event.
- When comparing amplitudes of different sensors, an initial normalization and baseline calculation are required due to variations of electrical components.

Regarding the creation of a baseline, several algorithms have been explored in the scope of this work. But before analysing different algorithms, the properties of a signal measured by an passive electric field sensor will be discussed.

Nearly all recordings shown in this work are sampled with a sampling rate of 50Hz. This is because in Europe, the operating frequency for power grids indoors is 50Hz. When

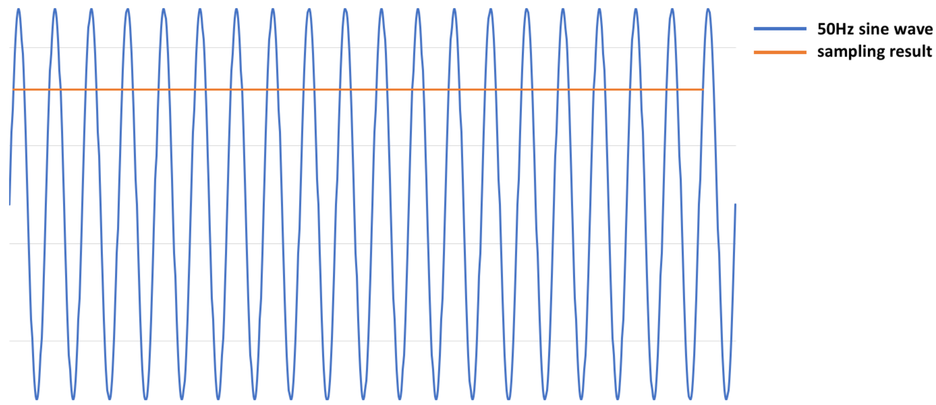


Figure 5.2.: A 50Hz sine wave, sampled with 50Hz and the resulting function

sampling a 50Hz sine wave with exactly 50Hz, the output function will be a constant. This holds true even when the sine wave is sampled with an initial delay, meaning with a phase shift greater than zero. Figure 5.2 shows such a 50Hz signal that was sampled with an exact 50Hz sampling frequency.

The advantage of this under sampling technique is that very slow ADC sampling rates can be used. Since modern ADCs support sampling rates up to several giga samples per second, as shown by Schvan et *al.* [67] and Greshishchev et *al.* [23], it is possible to acquire a large number of samples in this period of time. This enables the use of low pass filters to improve signal quality. A simple implementation of a low pass filter with multiple ADC samples is to average all collected additional samples.

Another advantage of the under sampling approach is that signal processing that is done after the measurement is very easy, in contrast to normal sampling after Shannon, where the interfering 50Hz frequency would have to be filtered out first. In applications where an absolute value threshold is used, signal processing can even be skipped completely. For many other applications, it is sufficient to remove the steady component of the signal, by computing the derivative of the original curve for example. The derivative on a discrete signal is a very inexpensive pre-processing technique computing wise. This makes it ideal for the use with Passive Electric Field data. In comparison to complex filters that remove the steady component, the derivative can be computed live for every new measured point of data, which is not possible if data first has to be buffered. The derivative for the n^{th} value is computed by:

$$\Delta f_n = f_n - f_{n-1} \tag{5.1}$$

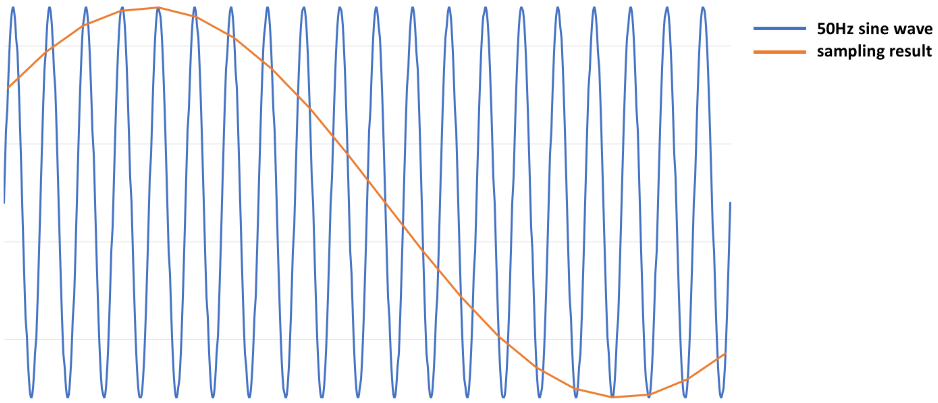


Figure 5.3.: Aliasing effect shown on a 50Hz sine wave

Which involves a single operation per value (function complexity $O(n)$) and a single integer, the value f_{n-1}, to be stored. These low requirements combined with the fact that many events recorded with an Passive Electric Field Sensor are rather short peak events than smooth curves (see Figure 5.1) are making the derivative an ideal pre-processing technique.

Problems with the under sampling technique arise if the frequency of the used analog to digital converter and the frequency of the interfering field are different. Just a slight difference in one of these frequencies will result in an aliasing effect, as depicted in Figure 5.3.

The 50Hz sine wave was sampled with a slightly lower frequency than 50Hz, resulting in a low frequency sine wave as sampled result. Because no clocks are absolute, no ADC can achieve a perfect result. Furthermore, the frequency of the electric power grid, the main source of disturbances when sampling Passive Electric Field data indoors, is not constant. The permitted mains frequency fluctuation is between 49.8Hz and 50.2Hz, but during fault conditions these values may be exceeded. That is the reason why aliasing effects as shown in Figure 5.3 when using under sampling with no further filtering are inevitable.

The formerly discussed pre-processing technique for removing the steady component of an Passive Electric Field signal by calculating the first derivative can be used for measurements containing aliasing effects. But for applications that involve the analysis of zero crossings of the measured signal by these kinds of disturbances are at a disadvantage. As shown in Section 4.2, the detection of zero crossings for Passive Electric Field data can play a crucial part for the detection of events. To compensate the falsely generated zero crossing of aliasing effects, additional pre-processing steps have to be implemented, for example as listed in Section 4.2.2.

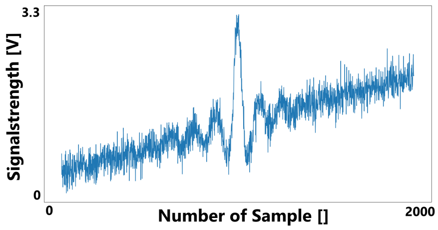
A different approach is to use more suitable baseline algorithms. The Fast Fourier Transformation, as proposed in the 1965 [54], one of the oldest signal processing algorithms still used today, is a fitting method to process Passive Electric Field data. Advantages of this algorithm are the low requirement of computing power needed ($O(n\log(n))$ instead of $O(n^2)$ as needed by the original Fourier Transformation) to perform the calculation and the fact that several, specific unwanted frequencies can be filtered at once. For Passive Electric Field data as recorded by the Linoc toolkit (see Section 3.2), these frequencies would be the steady component and very low frequencies that can occur because of aliasing effects (0Hz to 1Hz), as well as frequencies over approximately 15Hz, since human movement are located in this very low frequency domain. Disadvantages of the Fast Fourier Transformation is the fact that it requires a buffer of measurements. This means that the algorithm will have a fixed delay for incoming data. While this does not harm the ability to produce real time results, it means that an insensitive time exists whenever the Fast Fourier Transformation is used. This complicates the "online usage" of this algorithm (e.g. showing a filtered live plot of a sensor to be able to immediate observe the data). Another disadvantage is the buffer itself which can require a large amount of RAM that might not be available on embedded systems with micro-controllers lacking the proper amount of system memory.

This leads us to two simpler approaches to implement baselines for Passive Electric Field data that require very little RAM and have a run time behaviour of $O(n)$, which is even smaller than the Fast Fourier Transformation. These baselining approaches are therefore perfectly suited to be implemented for embedded systems.

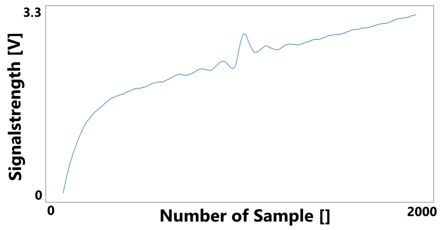
The first approach for creating a baseline with a Passive Electric Field Sensor as an input modality is to use a pair of a slow- and a fast-following function in form of exponentially moving averages. The slow-follower will follow the sensor inputs more passively than the fast-follower. Both functions can be derived as:

$$y(n) = x(n) \cdot s + y(n-1) \cdot (1-s) \tag{5.2}$$

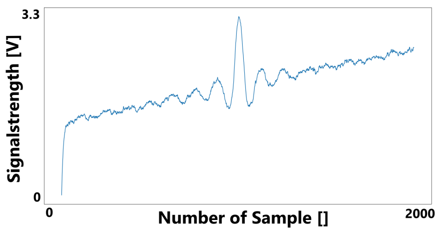
Where $x(n)$ is the n-th sensor value and $y(n)$ is the corresponding output of the follower function. $s \in]0,1[$ is the speed- or smoothness-factor of the follower function. Higher values for s mean a stronger tendency to follow the original sensor output, making it more prone to high frequency distortions. In the case where s would be equal to 1, the follower function would match the original input exactly, whereas if s equals 0, the follower function would remain a constant number. An initial value for $y(0)$ has to be provided and should be chosen in the region of the presumed baseline for faster convergence, although



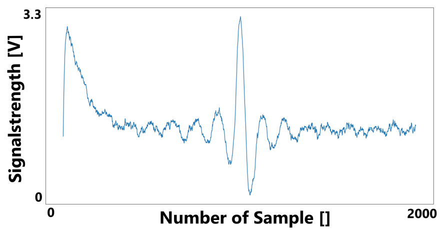
(a) Noisy signal



(b) Slow following exponential moving average, $s = 0.99$



(c) Fast following exponential moving average, $s = 0.9$



(d) Slow follower substracted from fast follower

Figure 5.4.: Smoothing a signal with two exponential moving averages

$y(0)$ can be chosen arbitrarily.

Figure 5.4 depicts how a noisy signal can be smoothed and baselined using two different exponential moving averages. The original signal as shown in Figure 5.4a exhibits a function with noise and a slowly rising baseline drift. Ideally, the calculated baseline for this signal would be a straight line with the same slope as the occurring baseline drift. Figure 5.4b and Figure 5.4c are both exponential moving averages, but with different smoothing factors to generate a function that follows the original signal slower and faster respectively. The result as presented in Figure 5.4d is the subtraction of the slow following function from the fast following function. It can be noted that the resulting function is less noisy than the original signal. In addition, the original upward trend was negated, leading to a function whose baseline is centered around zero.

In the shown example if Figure 5.4, the initial values of both the fast and the slow following function were chosen to be zero. This was done solely to demonstrate the convergence behaviour of the exponential moving average functions. Because of the time needed until both function converge sufficiently against the original signal, the result in

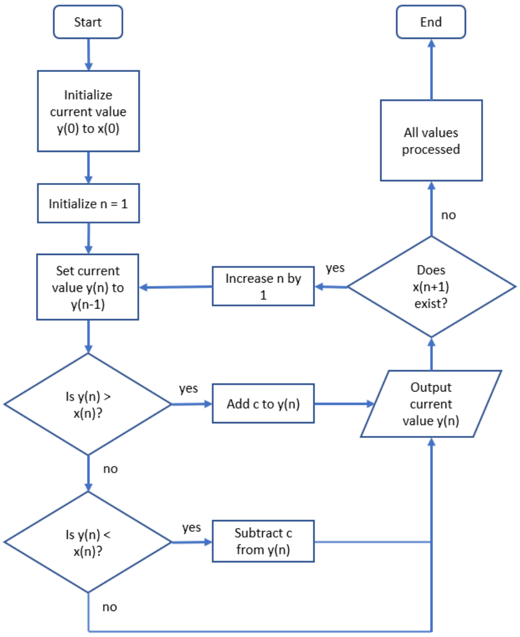


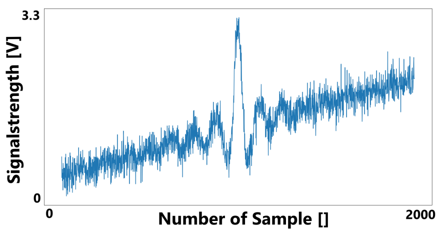
Figure 5.5.: Linear baseline algorithm

Figure 5.4d comprises a distortion at the beginning. This effect can be neglected, since a simple solution for this problem is to choose the first measured value of the original signal as initial value for both exponential moving averages, eliminating the time needed for convergence.

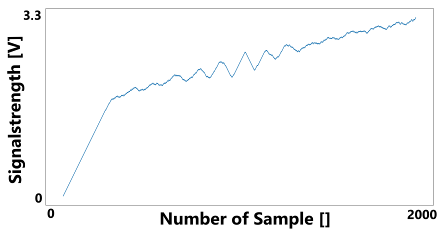
Because of its exponential nature, this kind of baseline approach also follows deflections of a curve that are not part of a baseline drift but are part of the useful signal that is to be extracted. This unwanted behaviour can be mitigated by replacing the first summand of Equation (5.2) with a constant. Since this would mean that the baseline generated by this new equation could only grow in one direction, a few more modifications have to be implemented.

Figure 5.5 shows the complete approach of limiting the growth of the baseline. The generated baseline will grow with a maximum of a constant c towards the original signal per measurement taken. The consequence is that the baseline will still filter out some of the wanted signal, but instead of removing a percental value of the wanted signal, the loss is now limited to an absolute value per measurement.

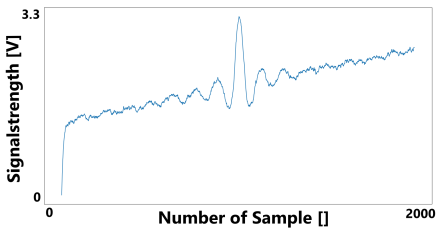
In contrast to Figure 5.4, the slow following baseline was replaced by a baseline gener-



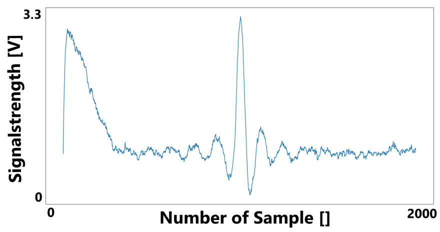
(a) Noisy signal



(b) Slow following linear baseline



(c) Fast following exponential moving average, $s = 0.9$



(d) Linear following baseline substracted from fast follower

Figure 5.6.: Smoothing a signal with an exponential moving average and a linear baseline

ated with the algorithm depicted in Figure 5.5. Again, just for the sake of demonstrating the convergence behaviour, instead of initialising the first value with the first value of the original signal (as demanded by the algorithm shown in the first step of Figure 5.5), the first baseline value was initialized with zero.

As it can be observed in Figure 5.6b compared to Figure 5.4b, the generated slow following baseline is converging less in the middle of the signal where a bigger amplitude is visible. But it is converging stronger on parts of the signal with smaller amplitudes. This means that the shown approach for calculating a baseline for a Passive Electric Field Sensor is more suitable in situations with strongly oscillating signals, while it is less suitable for signals of a more delicate nature. The information about what nature of signal is involved must be derived from the intended use case.

A disadvantage of generating a baseline with a limited slope is also the existence of scenarios in which the difference between the calculated baseline and signal is not decreasing or even increasing (divergence). While this is the normal and wanted behaviour of a baseline for sections of the signal with high deflections, it is a problem when occurring over longer periods of time because it indicates that the baseline slope is smaller than a potentially present baseline drift. This means that the constant c must be increased.

After separating the useful signal from the steady component with the discussed techniques, the absolute values of amplitudes can be compared. As already described in the preceding sections, an immediate comparison of amplitudes can make sense in scenarios where a discharge of the object of interest is unlikely.

5.2. Physical Optimizations

There are several considerations about the physical design of a sensor that have to be taken into account when using Passive Electric Field Sensing for different use-cases. As shown in Figure 3.4b and Figure 3.4a, one or two resistors are used in the structure of an Passive Electric Field Sensor. As already discussed, these resistors are responsible to steer the baseline of the sensor towards a desired, predefined value which is defined by the voltage in front of these resistors. R_{bias} behaves like a very slow pull-up resistor since it is, as discussed previously, chosen in the region of giga ohms.

Because the values of both R_{bias} are smaller than the input impedance of the instrumentation amplifier, these resistors are the dominant factor of the shown circuit when it comes to measurement range. This is because the small current, that is induced in the electrode of the sensor when an object is passing by, cannot be picked up by the amplifier if it is overwritten beforehand by the baseline current of R_{bias}. But increasing the resistance of R_{bias} or even removing it, meaning $R_{bias} \rightarrow \infty$, can render the sensor useless, since its tendency to run into a saturation scenario increases with the decrease of the baseline current.

This means that, in an optimal laboratory environment, where the induced current on the electrode is known, R_{bias} would be chosen as big as possible to increase the measurement range, yet so small that the sensor never reaches full saturation, to ensure maximum information gain. One can take this thought a step further and replace the fixed value of R_{bias} with an electronically controlled potentiometer. The biggest problem with this design is the unavailability of potentiometers within the needed ohmic range, since potentiometers or adjustable resistors are highly unusual with values over $10\text{M}\Omega$. But as shown in Figure 3.5, to setup a Passive Electric Field sensor with a measurement range of approximately two meters, resistor values in the giga ohm region are needed.

It should be taken into account that lowering the value of these resistors further, even if the sensor is not prone to run into saturation, might be useful to save steps in the signal processing afterwards. Even if there are no saturation issues in the currently relevant use-case, increasing the baseline current can dampen aliasing effects such as shown in Figure 5.3 and other external distortions of the signal. One should bear in mind that this technique will also lower the amplitude of the picked up signal itself. Hence, suppressing distortions with an increased baseline current is only applicable if the use-case generates a signal that is strong enough to compensate for this artificially created loss in signal strength.

To enhance the measurement range, instead of increasing the discussed resistors concerning the baseline current, another optimization that could be used is to simply enlarge the electrodes of the Passive Electric Field sensor. As discussed in Section 2.2, increasing the area of the electrodes will also increase the displacement current generated by moving objects and hence improve the SNR of the sensor. An enlargement of the electrodes is of course only feasible in applications where the spacial dimensions of the measurement apparatus are no concern, which eliminates nearly all mobile and embedded applications for example.

Other disadvantages of an enlarged electrode are similar to the disadvantages of choosing the value of the baseline resistor too high. As previously discussed, the baseline current is relevant to prevent saturation of the Passive Electric Field sensor. An electrode that is too large means that the baseline current is unable to compensate for currents it generates that are too strong, which in turn leads to saturation of the sensor and ultimately to loss of information.

A more obvious method for Passive Electric Field sensors to improve the signal to noise ratio of a sensor is to reduce the distance to the measured object. The two previous discussed measures, the enlargement of the electrode as well as the adjustment of the pull-up resistors for the baseline, both have an effect on the displacement current that is measured. This also holds true when reducing the distance to the measured object. Since the capacity of the formed capacitor is anti-proportional to its distance of the electrodes, as depicted by Equation (2.1), the displacement current can be increased by lowering their distance. Again, as for the enlargement of electrodes, this method to increase the SNR is highly dependent on its use-case and might not be applicable in scenarios where the objects of interest are strongly varying their distance to the sensor.

Another consideration when setting up a Passive Electric Field sensor is the shaping of the electrodes and their surroundings. Prance et *al.* showed that with efficient shielding, leakage-currents can be reduced to femto amperes [59]. Although shielding does not reduce the noise of the sensor itself, but rather the noise picked up from the environment. This means that the region of interest can be selected more precise by narrowing down the "field of view" of the sensor, as demonstrated in Section 4.2.

Since electrical field lines always enter and exit the surface of an electrode perpendicular, concentrating them is possible. Besides the efficient use of shields, Prance et *al.* also showed and example on how to focus the electrode of an Passive Electric Field sensor by using a needle with a 50µm tip [57]. A different approach instead of forming the electrode of the sensor itself is to couple the electrode to a different object that henceforth acts as electrode itself. Of course, the object that the sensor gets attached to has to have conductive properties to properly act as an electrode. This was for example demonstrated in Figure 4.1, where the sensor was installed on a whiteboard and then used to detect touches of a person on this whiteboard.

5.3. Summary

This chapter focused on answering RQ3:

Research Question 3 How can the use of Passive Electric Field Sensing be optimized?

Several techniques to optimize the use of this technology were discussed, including signal processing as well as hardware considerations.

Regarding the signal processing techniques it was discussed which parts of an Passive Electric Field signal transports useful information and which parts do not. Afterwards, known signal processing techniques were adapted for the utilization in the context of Passive Electric Field Sensing. This comprised the calculation of baselines, smoothing signals and considerations of the complexity of the used algorithms.

In addition to the algorithmic part of the signal processing, a description of which parts of an Passive Electric Field signal could be used under what circumstances was given. For the hardware optimizations, it was discussed which assembly groups of the sensor can potentially increase the SNR of the measured signal. These assembly groups included baseline resistors, electrode size and distance as well as the shielding of an Passive Electric Field sensor.

6. Conclusion

Before discussing the main contributions of this thesis, the terminology was clarified to distinguish Passive Electric Field Sensing from more common capacitive technologies that are also based on electrical field sensing. To this end, the origins of the passive electric field sensor have also been outlined in the literature. Chapter 2 also examined the physical principles to lay the foundation for the following chapters.

This thesis made several contributions to the research area of Passive Electric Field Sensing. These contributions were structured in three main research questions.

Research Question 1 Can Passive Electric Field data be collected in a manner that improves usability and deployment cost?

Research Question 1 was answered while contributing several improvements for Passive Electric Field Sensing to decrease deployment cost and increase usability. This was done primarily by the following contributions:

1. By eliminating the need for an ohmic connection to the electrical ground, the deployment of Passive Electric Field sensors was simplified since the wired connection to a nearby electrical outlet or a different source for electrical ground could be saved. It was demonstrated that the proposed solution also increased the overall measurement range of these sensors. This simplifies the deployment of the sensors even more because it increases the number of potential areas where a sensor could be placed.

2. With the introduction of "Linoc", a prototyping toolkit that focused on usability while maintaining the option for advanced users to create more sophisticated setups, it was shown that usability does not exclude flexibility while deploying Passive Electric Field sensors.

3. The deployment cost was even further reduced by showcasing how the overall number of sensors can be reduced while using this technology. This was accomplished by investigating several use-cases involving activities of daily living. For each use-case,

the performance of different sensor setups was compared with the conclusion that in most cases, a sensor setup containing less sensor can perform equally good or even better than a sensor setup that is comprised of every available sensor.

These contributions concluded Research Question 1 in a positive way because the usability and the deployment cost likewise can be improved at the same time. However, because the answering of RQ1 only involved activities of daily live as a use-case, the question arose for which other use-cases Passive Electric Field Sensing may be applicable, leading to Research Question 2:

Research Question 2 For which areas of application is Passive Electric Field Sensing feasible?

In the course of answering RQ2, this thesis contributed an experimental overview of Passive Electric Field Sensing by implementing different use-cases. The use-cases were chosen to maximize user interaction spread throughout the daily routine of a person. The use-cases included a whiteboard sensor, a door sensor, a traffic observation scenario, gesture recognition, a wearable implementation as well as a person counter. Even though the latter mentioned use-case was considered in more detail, this chapter did not elaborate the signal processing of Passive Electric Field Sensing further since its focus was laid on the application areas themselves.

That is why the last chapter addressed primarily the signal processing for Passive Electric Field Sensing. The discussion of the signal processing techniques in Chapter 5, lead to answering Reaserch Question 3:

Research Question 3 How can the use of Passive Electric Field Sensing be optimized?

This not only included the use of common signal processing techniques for the application with Passive Electric Field data, but also to several physical optimizations of the technology. It was debated how to improve the targeted sensing of use-case dependent relevant information by altering parts of the measurement hardware like baseline resistors and electrodes.

This concludes this thesis of Passive Electric Field Sensing for Ubiquitous and Environmental Perception. As depicted throughout all research questions, the potential for optimizations of Passive Electric Field Sensing as well as its application is still not completely exhausted. For future work, it may be worth while to further investigate the use of hardware filters for this kind of sensor, because the magnitude of the tiny currents measured prevented this from happening until now. As for the possible application areas, it may also be possible to use Passive Electric Field Sensing to transfer information in an energy efficient way by re-purposing low conductive objects of everyday use for this manner.

A. Appendix

A.1. Questionaire

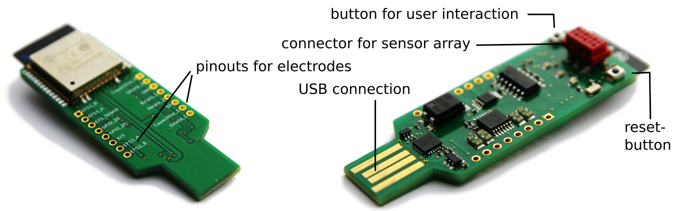
The following questionnaire was used in Section 3.2 during the user evaluation. It is comprised of a task section followed by a question section to evaluate the user-friendliness of the presented Linoc toolkit.

Evaluation of the Prototyping Platform for Capacitive and Electrical Field Sensing

TECHNISCHE UNIVERSITÄT DARMSTADT

1 Introduction

The Linoc toolkit is built for activity detection through electric field measurement and has two measurement techniques: capacitive and passive electric field sensing.
Its benefits are easy reconfiguration of sensor groups and connectivity without knowledge of embedded systems.



2 Setup

The Linoc sensor is connected to the computer via USB. The electrodes are connected to the pin-outs at the side of the board. Labels are on the bottom side of the chip.

2.1 Connection Setup

To communicate with the sensor a couple of steps are necessary.
Windows:
In the device-manager it can be checked if the Linoc is detected correctly. If this is not the case, the right device driver has to be installed from *www.ftdichip.com*. The connection is then made with the program Putty (*putty.org*).
After the installation, start Putty with the option *serial*, the com-port from the device-manager, a baud rate *115200* and without hard- and software control flows. Messages should now appear in the terminal.
Linux:
Start a terminal *(Ctrl+Alt+t)*. The current user has to belong to the group *dialout*
This can be checked with following command:
groups | grep 'dialout'
If the output is empty the user has to be added to the group using following command:
sudo usermod -aG dialout $USER
A reboot is necessary to apply the changes.
Linux & MacOS Communication happens easiest via Putty.
(if *Putty* is not available it can be installed with *'sudo apt install putty'*. Alternatives are screen, minicom, or other programs supporting serial connection). Putty is started with the option *serial*, the port (like */dev/ttyUSB0*) and a baudrate of *115200*
Messages should now appear in the terminal.

☐ setup was completed successfully ☐ setup was not necessary
☐ messages from sensor are displayed ☐ setup was not possible

2.2 Visualization (optional)

A graphical visualization helps understanding sensor values. A multitude of programs can be used for this. As example the Arduino IDE is mentioned here (*https://www.arduino.cc/en/Main/Software*). The respective port has to be selected in the menu 'Tools'. Afterwards the'Serial Plotter' can be started from the same menu.
The 'Serial Monitor' can be used to change the configuration.

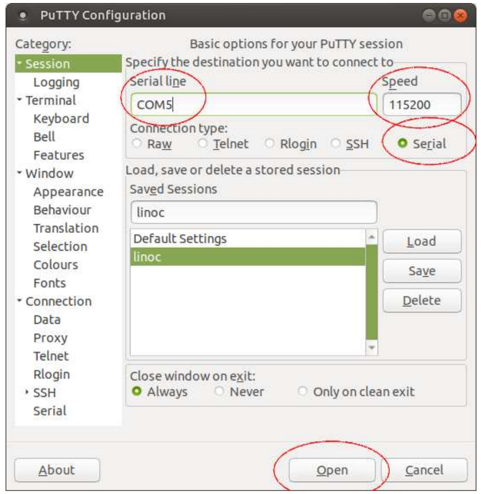


Abbildung 1: Putty window. relevant settings marked with circles

3 Configuration

3.1 Console

The configuration of the Linoc toolkit happens over a console. The console can be reached through pressing the button on the board, on the side with the connectors notch.
Typing *help* displays an overview of available commands.
☐ Console is displayed ☐ Commands are executed

3.2 Changing the Sensor Configuration

With the commands *capacitive_switch*, *eps_switch* and *frequency_set*, the sensor configuration can be changed. With *exit* the sensor returns to displaying values. *sensor_info* displays the current setup.

Please configure the sensor to the configurations described in the sections below and check if the values change if you move your hand towards the measuring electrode. For the configuration it might be necessary to change the placement of the electrodes on the chip.

3.2.1 Task 1: Configuration #1

Active sensors: Capacitive 1 & 2
Sampling frequency: 2 Hz
☐ Two value pairs are printed per second

3.2.2 Task 2: Configuration #2

Active sensors: EPS 1
Sampling frequency: 50 Hz
☐ Values appear noticeably faster

3.3 Task 3: Connect to Wi-Fi

Connect to the provided Wi-Fi hotspot and start a TCP server on the sensor.
Stop the connection again afterwards.
☐ connection established successfully. ☐ values can be queried from another device

4 Sensor Array

Multiple Linoc sensors can be connected to a sensor array (Daisy Chain).
The command to initiate is *'daisy_chain init'*.
Follow the instructions provided in the console from now on.
The connected devices takes the role of the master and queries sensor values of the other sensors.

4.1 Task 4: Sensor Array Setup

Connect 3 sensors with the provided cable to a sensor array

4.2 Task 5: Configuration

Follow the instructions in the console to setup all sensors.
☐ Number of sensors detected correctly ☐ Sensor values of all sensors are printed correctly

4.3 Break up the Sensor Array

Stop the sensor array. This is done with the command 'daisy_chain break'.
Check if the sensor can be used as before.
☐ Sensor array stopped ☐ Sensor can be used as before

5 Evaluation

Please answer following questions briefly:
Age: __ Years
Gender: ☐ F ☐ M ☐ n.b. ☐ n.A.
What is your current occupation: ☐ school ☐ study ☐ apprenticeship ☐ work ☐ something else

Which operating system are you using? ☐ Windows ☐ Mac ☐ Linux ☐ n.A.
Did you receive help with the tasks?: ☐ Yes ☐ No

Are you experienced in programming and/or computer systems?	○ strongly agree	○ agree	○ neutral	○ disagree	○ strongly disagree
Have you worked with similar toolkits?	○ strongly agree	○ agree	○ neutral	○ disagree	○ strongly disagree
Did you manage to fulfill the tasks with the information provided?	○ strongly agree	○ agree	○ neutral	○ disagree	○ strongly disagree
Did you at any time had the feeling to be overburdened?	○ strongly agree	○ agree	○ neutral	○ disagree	○ strongly disagree
Was the handling of the Linoc toolkit intuitive?	○ strongly agree	○ agree	○ neutral	○ disagree	○ strongly disagree
Do you think the functionality is sufficient?	○ strongly agree	○ agree	○ neutral	○ disagree	○ strongly disagree
Was the setup of the sensor array intuitive?	○ strongly agree	○ agree	○ neutral	○ disagree	○ strongly disagree

5.1 Free questions

What did you like about the system?

What did you dislike?

Could you imagine using the toolkit in a project?

Which applications can you imagine?

Which aspects should be improved?

What would facilitate the handling?

Further comments:

B. Publications

B.1. Full Conference Papers

1. Julian von Wilmsdorff, Malte Lenhart, Florian Kirchbuchner, and Arjan Kuijper. Linoc: A Prototyping Platform for Capacitive and Passive Electrical Field Sensing. In Rangarao Venkatesha Prasad, Nirwan Ansari, and César Benavente-Peces, editors, *Proceedings of the 10th International Conference on Sensor Networks, SENSORNETS 2021, Online Streaming, February 9-10, 2021*, pages 49–58. SCITEPRESS, 2021

2. Julian von Wilmsdorff, Biying Fu, and Florian Kirchbuchner. Improving Presence Detection For Smart Spaces. In *Proceedings of the 7th Workshop on Interacting with Smart Objects, Workshop on Interacting with Smart Objects, Valencia, Spain, June 2019*, pages 14–20. TUprints, 2019

3. Dirk Siegmund, Vinh Phuc Tran, Julian von Wilmsdorff, Florian Kirchbuchner, and Arjan Kuijper. Piggybacking Detection Based on Coupled Body-Feet Recognition at Entrance Control. In Ingela Nyström, Yanio Hernández Heredia, and Vladimir Milián Núñez, editors, *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications - 24th Iberoamerican Congress, CIARP 2019, Havana, Cuba, October 28-31, 2019, Proceedings*, volume 11896 of *Lecture Notes in Computer Science*, pages 780–789. Springer, 2019

4. Julian von Wilmsdorff, Florian Kirchbuchner, Andreas Braun, and Arjan Kuijper. Eliminating the Ground Reference for Wireless Electric Field Sensing. In Achilles Kameas and Kostas Stathis, editors, *Ambient Intelligence - 14th European Conference, AmI 2018, Larnaca, Cyprus, November 12-14, 2018, Proceedings*, volume 11249 of *Lecture Notes in Computer Science*, pages 90–99. Springer, 2018

5. Silvia Rus, Felix Hammacher, Julian von Wilmsdorff, Andreas Braun, Tobias Grosse-Puppendahl, Florian Kirchbuchner, and Arjan Kuijper. Prototyping Shape-Sensing Fabrics Through Physical Simulation. In Achilles Kameas and Kostas Stathis, editors,

Ambient Intelligence - 14th European Conference, AmI 2018, Larnaca, Cyprus, November 12-14, 2018, Proceedings, volume 11249 of *Lecture Notes in Computer Science*, pages 147–161. Springer, 2018

6. Lisa Scherf, Florian Kirchbuchner, Julian von Wilmsdorff, Biying Fu, Andreas Braun, and Arjan Kuijper. Step by Step: Early Detection of Diseases Using an Intelligent Floor. In Achilles Kameas and Kostas Stathis, editors, *Ambient Intelligence - 14th European Conference, AmI 2018, Larnaca, Cyprus, November 12-14, 2018, Proceedings*, volume 11249 of *Lecture Notes in Computer Science*, pages 131–146. Springer, 2018

7. Julian von Wilmsdorff, Florian Kirchbuchner, Biying Fu, Andreas Braun, and Arjan Kuijper. An Exploratory Study on Electric Field Sensing. In Andreas Braun, Reiner Wichert, and Antonio Maña, editors, *Ambient Intelligence - 13th European Conference, AmI 2017, Malaga, Spain, April 26-28, 2017, Proceedings*, volume 10217 of *Lecture Notes in Computer Science*, pages 247–262, 2017. BEST PAPER RUNNER-UP AWARD

8. Biying Fu, Florian Kirchbuchner, Julian von Wilmsdorff, Tobias Grosse-Puppendahl, Andreas Braun, and Arjan Kuijper. Indoor Localization Based on Passive Electric Field Sensing. In Andreas Braun, Reiner Wichert, and Antonio Maña, editors, *Ambient Intelligence - 13th European Conference, AmI 2017, Malaga, Spain, April 26-28, 2017, Proceedings*, volume 10217 of *Lecture Notes in Computer Science*, pages 64–79, 2017. BEST PAPER AWARD

9. Florian Kirchbuchner, Biying Fu, Andreas Braun, and Julian von Wilmsdorff. *New Approaches for Localization and Activity Sensing in Smart Environments*, pages 73–84. Springer International Publishing, Cham, 2017

10. Julian von Wilmsdorff, Alexander Marinc, and Arjan Kuijper. Context-Based Document Management in Smart Living Environments. In Norbert A. Streitz and Panos Markopoulos, editors, *Distributed, Ambient, and Pervasive Interactions - Third International Conference, DAPI 2015, Held as Part of HCI International 2015, Los Angeles, CA, USA, August 2-7, 2015, Proceedings*, volume 9189 of *Lecture Notes in Computer Science*, pages 382–394. Springer, 2015

11. Tobias Alexander Große-Puppendahl, Sebastian Beck, Daniel Wilbers, Steeven Zeiß, Julian von Wilmsdorff, and Arjan Kuijper. Ambient Gesture-Recognizing Surfaces with Visual Feedback. In Norbert A. Streitz and Panos Markopoulos, editors, *Distributed, Ambient, and Pervasive Interactions - Second International Conference, DAPI 2014, Held as Part of HCI Interational 2014, Heraklion, Crete, Greece, June 22-27,*

2014. Proceedings, volume 8530 of *Lecture Notes in Computer Science*, pages 97–108. Springer, 2014

12. Tobias Grosse-Puppendahl, Sebastian Herber, Raphael Wimmer, Frank Englert, Sebastian Beck, Julian von Wilmsdorff, Reiner Wichert, and Arjan Kuijper. Capacitive near-field communication for ubiquitous interaction and perception. In A. J. Brush, Adrian Friday, Julie A. Kientz, James Scott, and Junehwa Song, editors, *The 2014 ACM Conference on Ubiquitous Computing, UbiComp '14, Seattle, WA, USA, September 13-17, 2014*, pages 231–242. ACM, 2014

13. Julian von Wilmsdorff, Jan-Niklas Kolf, and Arjan Kuijper. Reducing Deployment Cost for Passive Electric Field Sensors. *Proceedings of 7th international Workshop on Sensor-Based Activity Recognition and Artificial Intelligence*, 2022. ACCEPTED, PUBLICATION PENDING

B.2. Journal Papers

1. Julian von Wilmsdorff, Florian Kirchbuchner, Biying Fu, Andreas Braun, and Arjan Kuijper. An experimental overview on electric field sensing. *Journal of Ambient Intelligence and Humanized Computing*, 10(2):813–824, 2019

2. Biying Fu, Florian Kirchbuchner, Julian von Wilmsdorff, Tobias Grosse-Puppendahl, Andreas Braun, and Arjan Kuijper. Performing indoor localization with electric potential sensing. *Journal of Ambient Intelligence and Humanized Computing*, 10(2):731–746, 2019

3. Julian von Wilmsdorff, Malte Lenhart, Florian Kirchbuchner, and Arjan Kuijper. Acquisition of EFS and Capacitive Measurement Data on Low-Power and Connected IoT Devices. In Andreas Ahrens, RangaRao Venkatesha Prasad, César Benavente-Peces, and Nirwan Ansari, editors, *Sensor Networks*, pages 104–124, Cham, 2022. Springer International Publishing

4. Julian von Wilmsdorff and Arjan Kuijper. Optimizations for Passive Electric Field Sensing. *Sensors*, 22(16), 2022

C. Supervising Activities

- Abdel-Al, Amany; Hofmann, Klaus [1. Gutachten]; von Wilmsdorff, Julian [2. Gutachten] - Long Term Observation and Data Analysis of Active and Passive Capacitive Signals

  Darmstadt, TU, Master Thesis, 2019

- Jakob, David; Kuijper, Arjan [1. Gutachten]; von Wilmsdorff, Julian [2. Gutachten] - Development of a Smart-Connection-Surface

  Darmstadt, TU, Bachelor Thesis, 2019

- Lenhart, Malte; Kuijper, Arjan [Supervisor]; von Wilmsdorff, Julian [Advisor] - Prototyping Platform for Capacitive and Passive Electrical Field Sensing

  Darmstadt, TU, Bachelor Thesis, 2019

- Ivanov, Ivelin; Kuijper, Arjan [Advisor]; von Wilmsdorff, Julian [1. Supervisor]; Kirchbuchner, Florian [2. Supervisor] - CapBed - Preventive Assistance System for the Bed Area Based on Capacitive Sensing

  Darmstadt, TU, Master Thesis, 2018

- Kolf, Jan Niklas; von Wilmsdorff, Julian [1. Gutachten]; Kuijper, Arjan [2. Gutachten] - Evaluation of Activity of Daily Life Recognition based on Electric Field Tokens

  Darmstadt, TU, Bachelor Thesis, 2018

D. Patent

The following patent was granted on the basis of publications that were published in the course of this thesis. The main claims of the patent involve improvements in the measurement of Passive Electric Field Sensing, which are mainly explained in Section 3.1 and Chapter 5.

(19) Deutsches Patent- und Markenamt

(10) **DE 10 2016 212 947 A1** 2018.01.18

(12) **Offenlegungsschrift**

(21) Aktenzeichen: **10 2016 212 947.3**
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G01B 7/00 (2006.01)
G08B 13/00 (2006.01)

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(56) Ermittelter Stand der Technik:

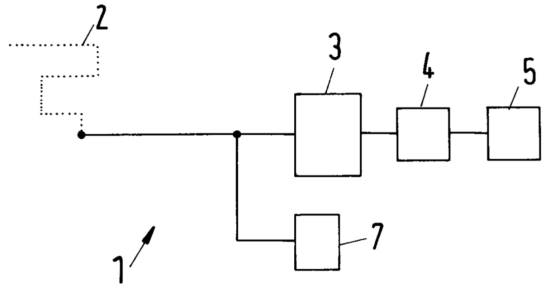
DE	**10 2013 219 340**	**A1**
DE	**11 2011 103 260**	**T5**
US	**2013 / 0 120 261**	**A1**

Prüfungsantrag gemäß § 44 PatG ist gestellt.

Die folgenden Angaben sind den vom Anmelder eingereichten Unterlagen entnommen.

(54) Bezeichnung: **Vorrichtung, System und Verfahren zur Aktivitätsdetektion**

(57) Zusammenfassung: Die Erfindung betrifft Vorrichtung zur Aktivitätsdetektion, wobei die Vorrichtung (1) zur Aktivitätsdetektion mindestens eine kapazitive Messeinrichtung und mindestens eine Auswerteeinrichtung (4) umfasst, wobei die kapazitive Messeinrichtung mindestens eine Messelektrode (2) umfasst, wobei die Vorrichtung (1) mindestens eine Vorladeeinrichtung (7) zur Einstellung eines Elektrodenpotentials (U_E) der Messelektrode (2) umfasst, wobei mittels der Vorladeeinrichtung (7) ein gewünschtes Elektrodenpotential (U_E) der Messelektrode (2) einstellbar ist, sowie ein System (17) und ein Verfahren zur Aktivitätsdetektion.



E. Curriculum Vitae

E.1. Personal Data

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E.2. Education

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2010 - 2013	Bachelor of Science, Major “Information Systems Technology”, Technische Universität Darmstadt
2006 - 2009	Bachelor of Science, Major “Computer Science”, Technische Universität Kaiserslautern
1998 - 2005	high-school diploma, Hans-Purrmann-Gymnasium Speyer

E.3. Work Experience

2015 - today	Fraunhofer Institut für Grafische Datenverarbeitung, scientific employee, hardware and firmware development
2014 - 2015	Fraunhofer Institut für Grafische Datenverarbeitung, technical employee, hardware and firmware development
2012 - 2014	Fraunhofer Institut für Grafische Datenverarbeitung, research associate, firmware development
2008 - 2018	self-employed business
2007 - 2008	Cartel Damage Claims, java developer for database applications

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