Algorithm for driver intention detection with Fuzzy Logic and Edit Distance

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***Abstract*—Driver intention detection is helpful to parameterize advanced driver assistance systems to reduce the warning dilemma and so to raise the driver's acceptance to such systems. An algorithm to predict driver's intention with Fuzzy Logic and Edit Distance is presented. The main features and the functionality is explained. The necessary steps for training the algorithm and the validation are presented. The performance of the first configuration is discussed and the future steps for improving the performance are shown.**

Keywords—driver intention detection; maneuver prediction; Edit Distance; Fuzzy Logic;

I. Introduction & Motivation

Driven by the vision zero, the vision for a reduction of serious injuries and casualties in road traffic [1] there is much work done on active safety systems. Advanced driver assistance systems (ADAS) played a main part in the last years to reduce the number of seriously wounded and killed people in road traffic [2]. These ADAS raise comfort and warn if critical situations occur and make it possible to intervene at a situation where the driver is not able to avoid a collision by himself [3]. The potential to avoid such collisions gets bigger if you provide a warning to the driver as early as possible so that he gets the chance to react to critical situations before an automatic collision avoidance system needs to be activated. But in that case the possibility of an unnecessary warning raises, e.g. the situation clears itself or the driver was fully aware of the situation and is able to clear that situation by himself. The driver may recognize these warnings as false alarms, which leads to the so called warning dilemma [4]. With a rising number of those subjective false warnings the system is recognized as annoying, which leads to a reduced warning character of the system [5]. So the aim would be to support the driver as good and as early as possible with a minimal number of unnecessary and false warnings [6].

Driver intention detection with a prediction of future human behavior may be one possible solution to reduce the number of false warnings and so conducting to solve the warning dilemma, if information about the driver's intention could be provided to the ADAS [5]. Driver intention detection focuses on the driver and measures features (early indicators) about performing a driving action e.g. a driving maneuver to predict a future behavior of the driver. A driving maneuver is an enclosed operation concerning the guidance of a vehicle [7]. A maneuver consists of a number of different actions a driver performs to conduct such maneuver. The driver intention belongs to the group of short term changing driver states which changes regularly within a few minutes or seconds [8]. It is not possible to detect the driver intention directly, but the actions a driver is performing in traffic situations can be set in relationship to performed driving maneuvers and inferred with observations to deduce the future behavior of the driver.

There are many motivators which influence the driver by forming his intention. Motivators may be the desire to drive safe and comfortable to his chosen destination [9]. There are also inhibitors which restrict the driver in his behavior, like the characteristic of the road, the weather or other road users. To infer the driver's intention these motivators and inhibitors have to be measured and have to be put in reference to each other. This combination can be interpreted as a mental representation or a mental model of the driving behavior. With such mental model it is possible to infer the driver's intention.

The driver's intention influences the behavior of the driver on the three levels of vehicle guidance [10]. On the strategic level e.g. the driver determines the route to go to his preferred destination. On the tactical level he performs actions like conducting driving maneuvers to reach his strategic goals. On the operational level he stabilizes the vehicle to perform the tactical maneuvers. We want to concentrate in our work on the tactical guidance level with a time horizon of few seconds.

If the driver's intention is known with the time horizon of few seconds to the future, it is possible to improve the performance of an ADAS [8] to support the driver on the tactical guidance level, because unnecessary warnings can be suppressed and more user suitable warnings can be generated. It is possible to infer the driver's intention by using in-car Controller Area Network (CAN-bus) data [11] and decide if an early warning in a certain situation is necessary. If so a necessary warning could be intensified or else an unnecessary warning regarding the detected driver intention can be suppressed.

In addition to the driver's intention there are some other driver conditions which influence the driving behavior like drowsiness or distraction. If a driver is drowsy or distracted the behavior and the execution of the driving maneuvers will be different [8]. As this work is meant to concentrate on detecting the driver's intention, the drowsiness and distraction need to be kept at a constant level to detect behavioral patterns, which can be assigned directly to the driver's intention instead of drowsiness or distraction. To address all driver conditions including the cross-connections between them, they have to be studied while varying them in a controlled way.

II. Algorithm for driver intention detection

There is a history of research to predict the driver's intention with real-time algorithms. A summary of some work can be found in [9]. They divided the analyzed algorithms into discriminative (e.g. Support Vector Machine) and generative (e.g. Hidden Markov Models) methods, which are trained using examples and generating their knowledge inductively from experimental data collections, because a generating a full mental model deductively is not feasible, because of the high complexity. There is no known technology today to measure the driver's intention directly and predict the driver's intention exactly in every situation. So far only predictions with incorporated uncertainty are possible. The inference of the driver's intention can be done by measuring his behavior, building up a mental model of the driver and then predict the driver's future actions. Mentioning this, it is clear, that talking about the driver's intention this information is considered as probabilistic.

The goal was to build up a white box algorithm. A white box algorithm is a system, which can be observed at every time in contrast to a black box model, like an artificial neural network. Additionally the knowledge collected in a white box model can be extracted and interpreted for further research. With that requirement it is feasible to detect the driver's intention and to extract and interpret the learned model parameters for future research. Additionally the effort concerning the computation time and the detection accuracy should be in a good proportion to each other.

Concerning the design of an algorithm the input variables have to be selected, necessary transformations and calculations on the input variables and the desired output the algorithm have to be defined.

A. Select input variables

Concerning the motivators and inhibitors for driver action as mentioned before, data containing these factors had to be collected to infer the intentions by making observations of human behavior. It seems logical at first, that you can predict a driver's intention the best if you use all data you can gather. But regarding to Occam's razor [13] it is best to choose only the best input variables as features for an algorithm. So concentrating on fewer and stronger input variables leads to the best compromise between prediction quality and computational effort analog to [14].

Concerning the clustering of measurable features into driver, car and environment [10], this work focuses on the behavior of the driver. But all three clusters of features have to be considered, because they all influence the driver and his behavior. In this work the focus lies on in-build vehicle sensors and driver monitoring. The data was collected through the vehicle CAN-bus and an optical driver monitoring system with the ability to detect the driver's gaze behavior. There are more solutions on gathering data concerning the driver and his behavior, but because the reduction of driving comfort, which comes in hand with intrusive methods, only non-intrusive methods are used to collect the data necessary for this research.

If you want to infer the driver's intention you should focus on the directly measurable data from the driver himself. It is done in this work via driver monitoring. With the use of a non-intrusive eye-tracking system you can estimate the attention focus of the driver and estimate the main information he is collecting, because around 90 percent of the information a driver is gathering is done with his eyes [15]. Then there are signals which can be measured from the interaction between the driver and his car, e.g. the steering actions (steering angle, steering angle velocity) and the accelerator and brake pedal operations. With these actions the driver is guiding his vehicle on the operational level to perform the desired maneuvers on the tactical level. Looking at the car itself, there are signals which can be measured concerning the actual state of the vehicle, like the velocity, the lateral and longitudinal acceleration or the yaw rate. These are measurable reactions of the vehicle to the driver's inputs and were used by the driver as feedback to stabilize the vehicle. Outside of the vehicle the interaction between the ego vehicle and the environment can be detected. There are some features which can be measured with the equipped sensors of the vehicle like the time-to-collision (TTC) [16] to other road objects, a time-to-line-crossing (TLC) concerning the lane markings [17]. Furthermore the surrounding environment includes information about the layout of the road, the number and geometry of lanes on the road and traffic limits to give only a few examples.

B. Fuzzyfication of input variables

Regarding the requirements to design a white box model a feasible method is to use Fuzzy Logic. The theory of Fuzzy Logic was first described by [18]. The main theory will not be explained in the paper, but can be found in [18]. With Fuzzy Logic it is possible to design a control system by using expert knowledge [19]. Fuzzy Membership Functions (MF) are designed to reduce the range of the input variables to a defined number of sets, similar to the comprehension of a human expert about a technical system. Fuzzy logic itself is not able to deal with time series data without any adaptions, because in the classical design it calculates the output data from the actual input data without considering past results. With that in mind [12] proposed an alternative to be able to handle data with time series characteristics with Fuzzy Logic. The Fuzzy rules of this system are interpreted as states. Each state incorporates a Fuzzy rule. These states are connected together accordingly to their appearance in time creating a sequence of fuzzy rules through time.

The number of fuzzy MFs per input variable in this work were chosen with expert's knowledge and the boarders of the MFs are adapted with the use of data, collected in an experiment. This is similar to the work of [20] for building up maneuver specific Fuzzy MFs. All input variables were then analyzed for the regions with the most and less change concerning the derivation as seen in Fig. 1. The top graph shows the course of the steering angle during a lane change maneuver over time. At *t=0s* the vehicle crosses the lane marking with the front left wheel. The middle graph shows the steering angle gradient plotted over the steering angle for the identical maneuver. With this information it is possible to identify the regions of the input variable where the highest and lowest gradient is present. With that precondition more Fuzzy MFs could be generated, where the signal is changing fast, to raise the sensitivity of the algorithm and fewer Fuzzy MFs, where the signal is changing slowly, to reduce the number of Fuzzy MFs, leading to a reduction of the computational effort. This is done by splitting the course of the graph into equal sized integrals concerning their plain. With this transformation it is possible to learn the boarders of the Fuzzy MFs from data which can be seen in the bottom plot of Fig. 1. The number of the Fuzzy MFs is an open design parameter to optimize the performance of the algorithm concerning detection quality and computational effort.

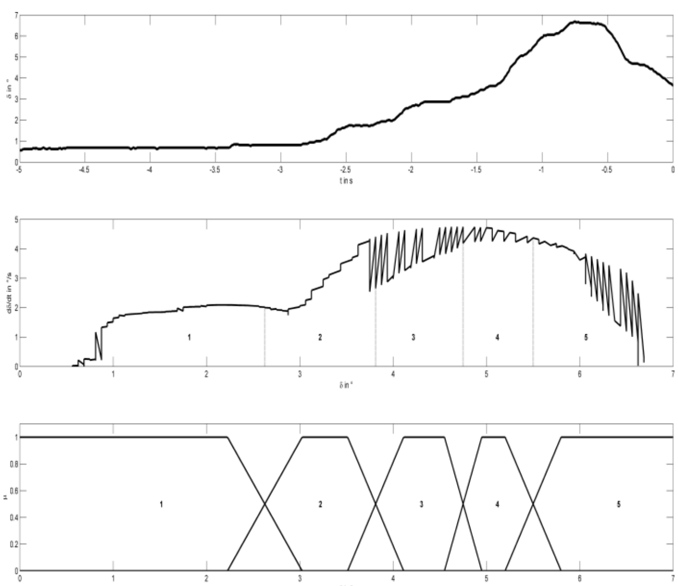

Fig. 1. Generating Fuzzy MFs from data

With the previous steps the boarders between the MFs were defined. To determine the exact course of all Fuzzy MFs the passages between the boarders have to be defined. A parameter was defined with a range of [0..1]. This parameter is the representation of fuzziness in the Fuzzy MFs. With a higher fuzziness you get smoother transitions between the Fuzzy MFs, but your system incorporates more fuzziness. This is an additional design parameter to be optimized afterwards.

C. Modelling the maneuvers with Fuzzy rules

The maneuvers to detect are located on the tactical guidance level. These maneuvers consist of different actions steps a driver is performing sequentially to conduct the guidance of the vehicle. So a maneuver can be interpreted as a sequence of actions over time. Each action can be expressed as a Fuzzy rule. The different Fuzzy rules, which are active during the maneuver steps are equivalent to states of a system which is a model of such maneuver.

To generate the sequences of states, which are characteristic for a certain driving maneuver, data from an experiment was used as training data. Every sequence is generated by automatically analyzing one maneuver from one participant at a time and consists of a various number of states. Every state inherits the active rule, the duration this rule is active and the mean Fuzzy aggregation value for that duration. This information can be expressed as a directed graph for extracting knowledge afterwards for further research. All sequences concerning similar maneuvers were stored into a maneuver specific database consisting of all sequences the drivers showed in the data. Rare behavioral patterns which may seem to be outlier to the usual behavior of the participants were considered and not rejected to get a greater span of data and so to get the chance to detect a greater variety of performing maneuvers.

D. Edit Distance

To infer the driver's intention, the actual behavior of the driver has to be measured and compared in real time with the sequence database. Because of inter- and intraindividual differences in performing driving maneuvers, no identical sequences were generated, because no participant showed the identical behavior in different repetitions of the maneuvers during the training process. So it is necessary to calculate a similarity between the real time behavior patterns and the learned sequences, because showing an identical behavior concerning our metrics is nearly impossible. Regarding the stated problem the Edit Distance is a feasible solution. The Edit Distance can be used for general feature detection concerning [21] and is used for word processing in [22]. In this domain it is used to calculate the minimal effort for transforming one word into another to determine the similarity of two words. This similarity measurement can also be used for maneuver prediction, because after the input variables were fuzzified and transformed into states, the methods from the word processing application can be used analogical. The transformation with Edit Distance is done by performing several operations, which have to be defined according to the special applications needs. For this application following operations seem to be feasible: the insertion of a new state, the replacement of a state with another and the removal of a state. To consider the temporal information incorporated in the sequences an appropriate operation was additionally defined similar to [23].

Every transformation step has some certain costs to be executed. The cost parameters are also design parameters to adjust the performance of the algorithm, concerning the desired performance criteria. E.g. the insertion of a state, which happens to exist more frequently in the database, is much cheaper than inserting a state which is represented very seldom. Non-existing states in the database get the maximal costs, according to that definition. The switching of two adjacent states is cheaper for states which are often next to each other than switching states which are seldom or never next to each other.

Another challenge is the comparison of sequences with different starting points. Because the exact starting point of a driving maneuver is unknown a continuous distance has to be calculated. The previously mentioned algorithms are not able to perform such a comparison, but with the adjustment [24] proposed it is possible to perform such transformation. Unlike a turning maneuver at an intersection, the driver can conduct a lane change maneuver at any time of his drive and any point on the road, unless the environmental conditions doesn't inhibit his intention.

E. State machine

To reduce the computational effort we interpret the databases as state machines. An example for a state machine can be seen in Fig. 2. There is one state machine for every maneuver, which is going to be detected. The state machine consists of the same states which are inherited in the sequence database, in this example 8 different states. The transitions between these states were extracted from the database. The Edit Distance for a certain maneuver is only calculated if the associated state machine is active. The state machine is marked active, when the predefined starting states were reached. In Fig. 2 the starting states are filled with grey color. The state-machine is deactivated when a maximum number of invalid transition is performed or the end state is reached (state no. 8 in Fig.2).

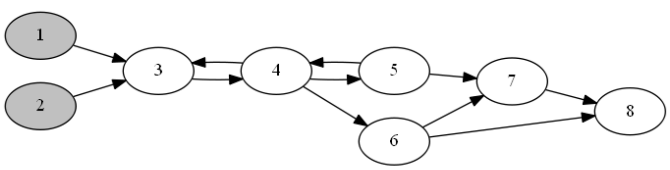

Fig. 2. Graphical representation of an example state machine

So at any time only the relevant similarities between the actual sequence and the sequences in the corresponding databases have to be calculated reducing the computational effort significantly.

F. Output of algorithm

The output of the algorithm provides the distance of the actual sequence the driver is performing in comparison to the stored sequences in the database. So it is possible to estimate quantitatively how similar an actual performed maneuver is compared with the maneuvers trained before. A geometric series is used to calculate the mean distance of the output vector with the distances to the sequences in the databases. So not only the smallest distance value to one sequence is considered for the maneuver prediction, but all of them with a certain weighting factor. This is considered to have the chance to detect a greater variety concerning inter- and intraindividual variations of maneuver executions. With the geometric series the greater the distance value the less it is considered in the calculations to balance the effect on the mean distance value. The distance measure correlates with the statistical probability, in this case the frequency of occurrence the maneuver is going to be performed by the driver. The correlation was extracted from the training data and stored into a look-up table. The transformation between these two values is calculated in real time by the pre-calculated look-up table. With using a look-up table in contrast to calculation the correlation in every calculation step we furthermore save some computational effort reducing the accuracy only by a small factor. In the same way the estimated probability is calculated, the estimated time horizon until the maneuver will take place can be extracted. The time horizon depends on the maneuver definition and a certain event which happens during this maneuver, e.g. the crossing of the lane marking during a lane change maneuver. The time horizon is as similar important as the estimated probability, because if you want to trigger an ADAS not only the maneuver which will be performed by the driver is important, but also the time when the maneuver will be conducted should be considered.

G. Design parameters of the algorithm

We got some design parameters to directly affect the performance of the algorithm as mentioned before. By defining the input variables you can change the earliness by using earlier input variables. Unfortunately earlier features often are less reliable for the detection. The turn switch activation is such an early feature. It is mostly activated before drivers are performing any steering action in a lane change maneuver, but sometimes drivers don't activate the turn switch at all. On the other hand the steering wheel angle is a robust predictor for detecting a lane change maneuver, but the time horizon to detect a lane change before it is going to be performed is much smaller compared to the information of the turn switch signal. So a combination of early and robust input variables are preferred to get a robust and early detection of the desired maneuvers.

With the number of fuzzy MFs per input variable you can affect the complexity of the system directly by enlarging the sequences of the learned maneuvers. If the number of input variables is raised more rules and states are generated. The length of all sequences will rise with the result of more computational effort for comparing the sequences. But on the other hand a finer resolution of the estimated probability and time horizon can be achieved.

By changing the fuzziness you can change the behavior of the system at the points in between the learned boarders of the Fuzzy MFs. A greater fuzziness leads to a greater diversity and gets the calculations more fuzzy so the outputs will be smoother, leading to a more continuously value of estimated probability and time horizon.

By changing the maximum time horizon you can change the overall length of the sequences in the database, leading to a greater possible prediction horizon of the state machines, if the signals provide such information. This comes in hand with a greater computational effort.

You can affect the output of the algorithm and the calculated distance by changing the costs of the transformation steps in the Edit Distance. The parameters should be changed with regard to each other, so that their relation will be consistent with the meaning of the transformation. The insertion of a previously unknown state should always be higher than switching two often appearing states. The variation of the costs will not influence the computational effort but the output of the algorithm and can be used to raise the detection accuracy without raising the computational effort.

III. Experimental Validation

To gather data to build our algorithm the Adam Opel AG in cooperation with the Institute of Ergonomics and Human Factors from the Technische Universität Darmstadt conducted a controlled field study on a closed airfield in the UR:BAN research project [25]. 44 participants were instructed to drive 10 laps through a predefined and setup round course. The participants had to perform several normal maneuvers (e.g. lane change) as well as critical maneuvers (emergency braking). Some detail can be found in [26] and [27]. A controlled field study gives you the ability to study human behavior repeatedly under similar conditions. So the behavior could be studied without getting too much cross influences from other aspects, e.g. different other traffic participants during the test, except these which are performed controlled by the study design. Additionally the distraction of the drivers was reduced to a minimum and the drowsiness was kept constant over the experiment to reduce the influence of these driver states to the intention.

A. *Validation of the algorithm*

The algorithm was trained and tested with data from the controlled field study. For the first validation it was trained with data of 7 randomly selected participants and tested with data of 3 other randomly selected participants, consistent with the recommendation for machine learning in [28]. The design parameters were then systematically varied to find the optimal parameter set for the algorithm. At this stage the algorithm was trained to detect lane change maneuvers to the left and right, stopping maneuvers at intersections and emergency braking and evading maneuvers in urban traffic situations.

B. *Performance measures*

As performance measures the specificity and sensitivity were used [29]. For calculating those numbers the true and false positive and the true and false negative ratings of the algorithm have to be gathered. It was not feasible to calculate the true negative count, because of the non-uniform distribution of events in the different classes [30]. So the number of maneuvers the participants have performed through a whole lap in the experiment were estimated and multiplied by the numbers of laps and all participants to make an integer estimation on how often the prediction scores a true negative hit. With these numbers we are able to create a Receiver Operating Characteristic (ROC) [31], concerning the performance of the algorithm for a binary classifier with a varied activation threshold. In Fig. 3 you can see the ROC-curve for the prediction of a lane change maneuver to the left. The algorithm was trained using the steering wheel angle, the steering angle gradient and the TLC as input variables. With this information it is possible to decide at which estimated probability a binary classifier should decide to toggle an ADAS regarding the optimal tradeoff between specificity and sensitivity. In this case the value for the estimated probability is $p = 78{,}4\%$. If you want to provide an digital information to an ADAS a value below 78,4% should be marked as no intention to perform a lane change maneuver and as soon as the value raises over 78,4% the information, that the driver is going to perform a lane-change maneuver should be provided.

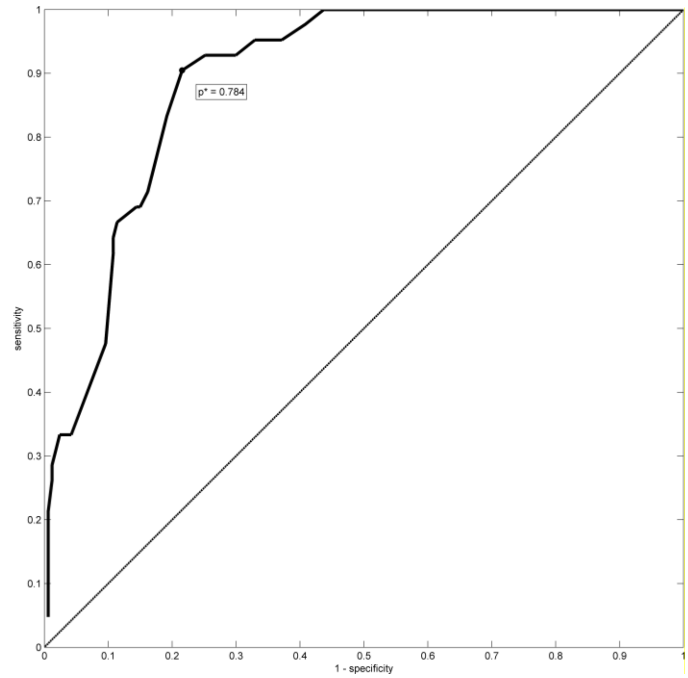

Fig. 3. ROC-curve for prediction probability of lane change maneuver

The accuracy of the predicted time horizon was calculated with the data by using the mean quadratic error between the estimated and the measured value. The earliness of the prediction was another validation point, because the earlier a maneuver can be predicted the earlier a warning or an intervention of an ADAS can be triggered giving the driver more time to react to critical situations.

IV. Conclusion

We presented our algorithm for inferring the driver's intention concerning the planned tactical driving maneuvers in urban traffic situations. With a prediction time horizon of some seconds it is possible to parameterize warning and intervening ADAS to perform a driver suitable action. It would be feasible to present a warning at an earlier time to the driver or to suppress unnecessary warnings and actions from an ADAS regarding the traffic situations. There is a potential to reduce the warning dilemma with this algorithm so the effectiveness of modern active ADAS could be raised.

The next steps include identifying the best set of input variables for the algorithm regarding the desired maneuvers and situations. The training for additional maneuvers to detect e.g. turning maneuvers at intersections is possible, because the algorithm is able to detect those maneuvers it is trained for, with the corresponding data. Also the optimization of the design parameters is not yet completed to its full capacity, giving the chance to the raise the performance of the detection furthermore. After finding the best combination of input variables and algorithm parameters the training of the algorithm will be extended to all 44 participants of the experiment.

Also by addressing a defined ADAS the prediction of the detection can be optimized to a certain probability value or to a needed time horizon. E.g. for an ADAS with automatic collision avoidance with braking and evasive maneuvers the information about the driver's intention is needed before the last decision point in time where the system intervenes, to avoid a collision, where braking and an evasive maneuver are still physically possible. Further research should also include the influence of drowsiness and distraction to driver's intention with the aim to infer the intention for drowsy or distracted drivers, leading to a more general algorithm to detect driver's intention.

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