# An adaptive assistance system for subjective critical driving situations: understanding the relationship between subjective and objective complexity

*Alexander Lotz[1], Nele Russwinkel[2], Thomas Wagner[1], & Enrico Wohlfarth[1]*
*[1]Daimler AG, [2]Technische Universität Berlin*
*Germany*

**Abstract**

Partial and conditional automated driving allows the driver to transfer responsibility to the vehicle. While assistance systems are designed to deal with aspects of the driving task, currently no assistance systems are available to predict driver behaviour for take-over when the vehicle is handling the driving task. This is important as drivers might interpret driving situations differently than an activated automation function. This can cause self-initiated take-overs leading to a reduction of trust in the system. In theory, if a prediction is robust, an assistance system could also adapt based on this prediction. A new subjective complexity model addressing these situations is introduced. The subjective complexity model learns situations in which individual drivers have previously self-initiated control of the driving task. Based on exemplary sideswipe manoeuvres, the system concept is explained and simulated with a training and test dataset. Upon introducing this system, a discussion is initated on the difference between objective and subjective situation complexity. A distinction is drawn between mathematical descriptions based on vehicular sensor data and human interpretation of the environment. The proposed system also functions as a carrier technology for further investigations between the differences of objective and subjective complexities.

**Introduction**

The driving task consists of many short-term decisions, e.g. steering to hold vehicle in lane, and long-term decisions, e.g. route navigation. Different factors need to be considered in order for the driver to successfully solve these tasks. Therefore, it is important to understand which aspects are considered complex. This can help to include, enhance or adjust assistance accordingly. At the same time, humans are decisively influenced by the environment, which they encounter and thereby confined in their range of interactions. With various developments in the field of automated driving, possibilities of directing attention away from the driving task will become possible. In Level 3 (SAE J3016, 2018) the driver can focus on non-driving related tasks, but needs to regain control of the vehicle when warned. Recent research regarding take-over behaviour has shown that environmental factors such as traffic density and time-budget (distance to objects) play a crucial role in successful take-over capability for Level 3 (Gold, et al., 2016; Lotz, et al., 2019; Zhang, et al., 2019). There is a large variety of definable environmental factors, making it difficult to

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pinpoint isolated factors to varying driver take-over behaviour. When revisiting traffic density as an exemplary factor, other environmental factors such as time to collision, number of lanes and colour of vehicles can form interaction effects. Multiple isolated environmental factors can merge to form singular driving situations through the relation of several of these factors over time. Arbitrary measures, such as low or high traffic density, also make a comparison difficult. However, the driving environment can be measured with a variety of different sensors mounted on a vehicle. Based on the chosen sensor setup, this creates a representation with a sensor-specific degree of detail of environmental factors or higher-level situations. As a driver also perceives the environment with her/his senses and develops a representation of the situation, influences of environmental factors such as traffic density on the driver can be compared and deduced. If a certain driver reaction is linked to an environmental factor, based on the sensor representation of the environment an assistance system could possibly predict driver behaviour. This information would especially be valuable in the abovementioned take-over situations, in which responsibility shifts from the machine to the human. The mathematical description of the environment could be attributed to subjective complexities, identifying scenarios that cause higher workload and situations in which the driver needs assistance. As there are possibly also inter- and intra-individual differences in perceived subjective complexity, an ideal assistance system would adapt individually and specific to different driving situations. This could lead to a better usability, correct allocation of assistance and acceptance of automated driving function.

Sensors such as cameras, radars and lidars collect data that describe an abstraction of their perceived environment and allow interpretation either through humans or computational algorithms. In a simplistic form, this data collection is similar to the cognitive processing for the first perception phase towards building situation awareness (Endsley, 1995). In what terms does environmental complexity differ mathematically (objective complexity) to an individual perceived situation complexity (subjective complexity) and how can this be measured? The second part of this question will be addressed in this paper and a solution will be developed to enable the investigation of the first part of the question in future work.

It is worth defining our interpretation of these two different versions of complexity, explicitly regarding driving environments. *Objective complexity* is the mathematical describable driving situation in which all objects within a predefined area are continuously referenced to an ego-vehicle. This mathematical description includes metrics such as the distances, velocities (relative and absolute) and the time to trajectory intersections. The mathematical composure of the factors can vary and yield different values of objective complexity depending on the interpretation of the mathematical description. In a practical example, the data would be obtained from singular or combinations of sensors, capturing information of environmental objects. This differs from general global descriptions of complexity such as the number of vehicles in the environment (Gold, et al., 2016), in which no references to an ego-vehicle and driver are drawn. The problem with global descriptions, without reference to the driver in the environment, is that the dispersion of vehicles is not evident from the point of view of the driver. When listing the amount of vehicles surrounding the ego-vehicle, no information is given where all these vehicles are (front, behind, lane etc.). *Subjective complexity* is the perceived complexity of a driving situation from the human's perspective. This includes all stationary and moving objects relevant to the driving task. Abstract cognitive and psychological constructs such as driving situation familiarityaffect this complexity and are not measureable with similar accuracy as the metrics of objective complexity. This is mainly because measurements from designated sensors such as electroencephalography, skin conductance or any other psychophysiological measurement are not unambiguously linked to any of these constructs and quantification of human response is not possible. A scale for the subjective complexity is also arbitrary, relative to the psychological constructs and subject to individual differences.

Previous research has focused on describing environmental factors specifically for the driving environment, such as the time to resume control and the quality of the transition depend on driver-vehicle-environment factors (Gold, et al., 2016). Early work resulted in a classification scheme of driving situations with three million unique situations (von Benda, 1977). This classification scheme was later simplified to incorporate only four major aspects; horizontal course, traffic density, special weather and hazards (Fastenmeier, 1995). Due to the high complexity of factors, different types of models have been introduced to predict driver transition behaviour. The first class of models utilizes mathematical models, e.g. regression models, to extrapolate data based on empirical findings post-hoc and explain correlations in the data (McDonald, et al., 2019; Zhang, et al., 2019). A second class of models provides online prediction based on data obtained through driver and environment monitoring (Nilsson et al., 2015; Braunagel et al., 2017; Lotz & Weissenberger, 2019). However, subjective driver interpretation is missing as input data. The problem with all of these models is that defined factors can interact, e.g. traffic density or driver experience, effects that cannot be investigated in isolation within one study. Therefore, the investigation of differences between objective and subjective complexity, as defined above, has been difficult in the past. The investigation was especially difficult as drivers continuously needed to control the vehicle, always generating a response at steering. This has now changed through automated driving.

Subjective relevance is an important factor to predict individual behaviour. Ohn-Bar and Trivedi (2016) conducted research on the subjective relevance of objects in the driving environment, stating that spatio-temporal reasoning is needed to identify relevance by the driver. Therefore, the context of space and time in the driving situation of any automation level should be regarded when investigating environmental effects on the driver.

Through recent technical advances of automated driving, it is possible for the driver to take their hands off the steering wheel and observe the environment. Automated driving, specifically Level 2 and Level 3, is an ideal enabling technology suited for the investigation of differences between objective and subjective complexity. Therefore, it is possible to gather data on subjectively perceived critical complexity where previously the driver continuously generated responses at the steering and the data were open for interpretation. A distinction of intended interventions was difficult, because drivers constantly had their hands on the steering wheel.

This paper introduces a conceptual advanced driver assistance system. The system is designed to learn situations in which the driver takes back control of the self-driving vehicle, when no request to intervene is issued. The assistance system thereby registers situations based on current objective complexity from the vehicular sensors and associates it with subjective complexity. The moment drivers reclaim control through self-initiated take-over, the objective complexities gathered by vehicle sensors can be identified in which no automated driving is desired. Thereby, the assumption is formed that the drivers consider the environment as subjectively complex. Hence, the automated vehicle can learn when the automation function itself can suggest take-over predictively.

## Subjective Complexity Model

The proposed subjective complexity model relies on the fact that the vehicle has a driver assistance system capable of simultaneous lateral and longitudinal control, i.e. without the need of having the hands on the steering wheel. Typically, this approach is only possible with advanced Level 2 or Level 3 systems. The objective of the proposed model is to make predictions when the surrounding driving complexity reaches a point in which the driver feels intervention is necessary. Thereby, a relationship between objective and subjective complexity can be investigated. The hypothesis is followed that the driver subjectively decides that complexity of the driving environment is too complex and external vehicular sensory data is recorded at intervention. Other reasons for self-initiated take-over are also possible, e.g. low satisfaction with vehicle control, and intention cannot be differentiated. It is worth noting, that the trust in the automated vehicle is affected by driving experience (Gold, et al., 2015). To show the functionality of the model, sideswipe manoeuvres were recorded with an advanced Level 2 automated truck and divided into a training and test dataset. These sideswipe manoeuvres were limited to vehicles crossing onto the ego-lane from the fast lane (left).

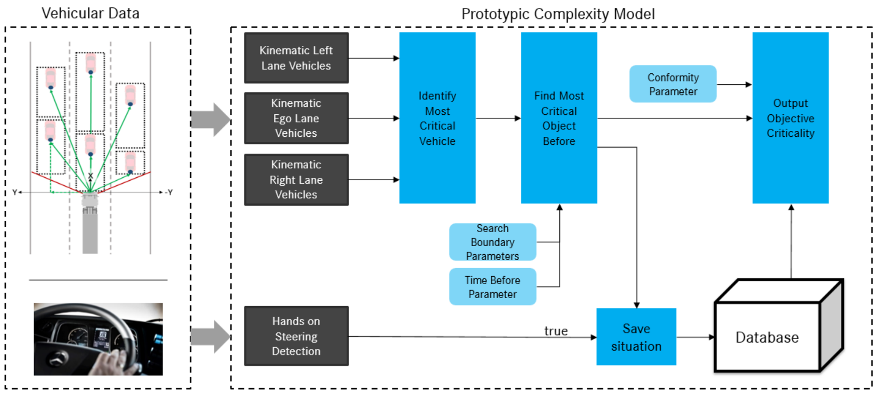


*Figure 8. Workflow of adaptive assistance system. Sensor data are split into regions of interest (left, ego, right). Kinematics of all perceived objects in these regions are calculated upon which the most critical objects is identified (see Figure 2). Output criticality is calculated based on previously recorded data.*

*Concept*

The functionality of the subjective complexity model is presented in Figure 1. The model is split into four major components. First, the perception of vehicles in the periphery of an ego-vehicle are identified, including the calculation of kinematic relationships. Secondly, the most critical object is determined based on the previously calculated kinematics. Thirdly, situations in which the driver intervenes with the vehicle without a take-over warning being displayed, are recorded and saved in a database. Fourthly, the criticality of current driving situations is calculated based on the conformity parameter of current kinematics with saved situation kinematics.

*Sensory perception and kinematics*

Sensory data of the surrounding vehicles are gathered and split into three possible lane positions. This includes the ego-lane as well as the lanes directly to the left and right. The raw data received from the sensors includes the lateral $Dist_y$ and longitudinal $Dist_x$ position as well as the speed of each object relative to the ego vehicle $RelSpd$ and object width $Width_y$. This allows the calculation of lateral $Spd_y$ and longitudinal $Spd_x$ speed of each object. Additionally, a safety corridor is defined through the width of the variable $Buffer$, see Figure 2. In this version of the proposed model, a maximum of six vehicles could be perceived around the ego-vehicle, with a maximum of two objects per lane. It should be noted that different sensor setups can alter the outcome of the system dramatically. By adding different sensors, e.g. cameras for object classification, additional data can offer subsequent critical object identification. Based on available radar data with the current sensor setup, the following kinematic variables were calculated.

$$TT_{cross\_border} = \left( \frac{\left|Dist_y\right| - \left(\frac{1}{2}\left(Width_y\right) + Buffer\right)}{Spd_y} \right) \quad (1)$$

$$TT_{headway} = \frac{Dist_x}{RelSpd} \quad (2)$$

$$TT_{collision} = TT_{headway} - TT_{cross_{border}} \quad (3)$$

$$Dist_{cross\_border} = TT_{cross\_border} * RelSpd \quad (4)$$

In total, ten kinematic variables are taken into account with the available sensors, see Table 1. Every relevant object on any of the three lanes has a separate set of these ten variables. Further variables in following implementation versions could include crossing angles, further crossing times, trajectory predictions.

*Identification of most critical object*

In the case of a self-initiated driver take-over, i.e. no request to intervene, either the complete constellation of the surrounding vehicles or a single object causing the driver to intervene needs to be identified. Here an assumption needs to be formulated, to differentiate between these two options. The proposed model assumes that one object is the most critical in the environment and it can be defined as the object that would enter the safety corridor first, if all vehicles maintain their trajectory. This assumption corresponds to the smallest $TT_{collision}$, see equation (3), of any of the six surrounding objects. Previous development versions of the adaptive model also incorporated multiple critical objects. However, as there is always one object which is hit prior to all the others, the assumption was made that the driver reacts primarily towards this object. If the constellation of all vehicles were to be recorded, a higher amount of constallations would be possible with less likelihood of reoccuring.

*Recording self-initiated take-over situations*

If a driver intervenes with the automation function controlling the ego-vehicle, the currently most critical object is recorded to a database. Simultaneously, the model identifies where this most critical object was located for a certain amount of time previously to the take-over. The time is an adjustable parameter as well as the size of the search region, defined by a lateral and longitudinal measure. The two sets of ten kinematic variables, current and delayed, are saved with object lane positions resulting in 22 mathematical variables. Every time the driver regains control of the vehicle, the current situation with its delayed prior position is recorded to the database. As the driving environment can vary dramatically based on the type of road or national restrictions, the data and type of driving culture are completely adaptable. Similarly, the driver's interpretation of situations may vary over time and compared to other drivers. As more and more data is recorded the model adapts over time, this enables learning of personalized self-initiated take-over.

*Table 2. Kinematic variables calculated from sensor data.*

| Variable Name | Definition |
|---|---|
| $\boldsymbol{Dist_x}$ | Longitudinal distance from front of ego-vehicle to rear of object. |
| $\boldsymbol{Dist_y}$ | Lateral distance from front of ego-vehicle to rear of object. |
| $\boldsymbol{Spd_x}$ | Longitudinal speed of object relative to the longitudinal axis of the ego-vehicle. |
| $\boldsymbol{Spd_y}$ | Lateral speed of object relative to the lateral axis of the ego-vehicle. |
| $\boldsymbol{EgoSpd_x}$ | Speed of the ego-vehicle along its longitudinal axis. |
| $\boldsymbol{RelSpd}$ | Difference of longitudinal speed between the object and the ego-vehicle |
| $\boldsymbol{TT_{cross\_border}}$ | The time required for the object to cross into the safety corridor. Only considered if the trajectories of the vehicles cross. |
| $\boldsymbol{TT_{headway}}$ | The time required for the ego-vehicle to bridge the longitudinal distance to the object. |
| $\boldsymbol{TT_{collision}}$ | The time required for the ego-vehicle to reach the point where the object crosses into the safety corridor minus the time required to reach that point. This measure considers the time to collision once the safety border is breached. |
| $\boldsymbol{Dist_{cross\_border}}$ | The longitudinal distance the object is from the ego-vehicle once the safety corridor is breached. |

*Continuous Criticality Output*

Upon identifying a most critical object, the model relies on fuzzy logic (Ross, 2010) to compare current situations with previous unforced take-over situations from the abovementioned database. All kinematic variables are taken into account for the prediction method and a majority voting mechanism determines comparability of saved situations with the current driving environment. It is possible to adapt to this mechanism in the future. The model searches through all previous situations, comparing current kinematic variables to the saved situations. As it is highly unlikely that the exact situation appears twice during an self-initiated take-over, a confidence percentage in form of a conformity parameter is introduced. The definition of this confidence percentage has a profound influence on the precision of the model as discussed in the conclusion.

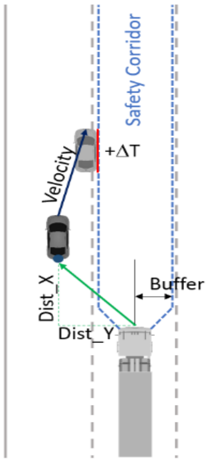


*Figure 9. Overview of distances and variables for kinematic calculations. The vehicle on the left lane requires $\Delta T$ time, corresponding to $TT_{cross\_border}$, to cross into the safety corridor on the ego-lane in front of the ego-vehicle.*

*Data Collection*

To present the functionality of the subjective complexity model, a small number of manoeuvres were recorded on a German two-lane federal road with speed restrictions. This dataset is too small to investigate the full potential of the system. However, first indications of the functionality can be examined. The sensors were mounted to a prototype Mercedes-Benz Actros with an Active Drive Assist (Daimler AG, 2019). Over the course of two hours, sideswipe manoeuvres from the left lane towards the ego-lane were recorded. This manoeuvre was an exemplary situation, which our fictive driver was uncomfortable in and chose to take-over. It can be expected that real-world traffic situations in which a driver intervenes with the automation function are seldom and would not deliver adequate data. The dataset was divided into a training and test dataset with proportions of approximately 90% to 10% respectively.

This resulted in a total of 105 training sideswipe manoeuvres, see Figure 3, and 13 test manoeuvres.

**Results**

The model is evaluated based on the self-initiated test manoeuvres that are examined qualitatively. These 13 test manoeuvres are not limited to sideswipes, they consist of take-overs due to a construction site, one sideswipe in a traffic jam at low speeds, five delayed take-overs due to sideswipes and six sideswipes from motorway entry-ramps, i.e. right side. A qualitatively comparison of vehicular signals synchronised with a dashcam video was realized for the model proof of concept. A quantitative analysis was not meaningful, as the data are limited. The complete model was simulated in MATLAB/Simulink, see Figure 4 and Figure 5, which depict the prediction value of the most critical object currently and delayed as well as the hands-on signal when the driver intervened.

*Figure 10. Exemplary sideswipe manoeuvres recorded in the training dataset.*


*Figure 11. Two exemplary self-initiated take-over situations that were not trained in the training set. Predicted sideswipe manoeuvres never reach a confidence greater 80%.*

Figure 5 displays the qualitative comparison of the five sideswipe manoeuvres, which the driver initiated with a varying delay. As shown in the graphs portraying the current similarity prediction, delayed similarity prediction of 0.5 sec and when the take-over was initiated (top to bottom), the snapshot of the actual sideswipe was predicted very accurately (vertical blue line). Overall, in four of the five delayed take-overs, the model correctly identifies a sideswipe manoeuvre with 100% confidence. The third depicted sideswipe take-over in Figure 5 with a delayed response shows a low prediction quality. It can also be seen, that sensor dropout appears quite frequently throughout the drives.

The self-initiated take-overs that were not included in Figure 5 and consisted of the six take-overs from sideswipes at motorway entry-ramps, displayed a poor quality of prediction and are not depicted. Overall take-over prediction value by the model in these other eight situations never reached over 80%. Two of these eight exemplary situations are depicted in Figure 4.

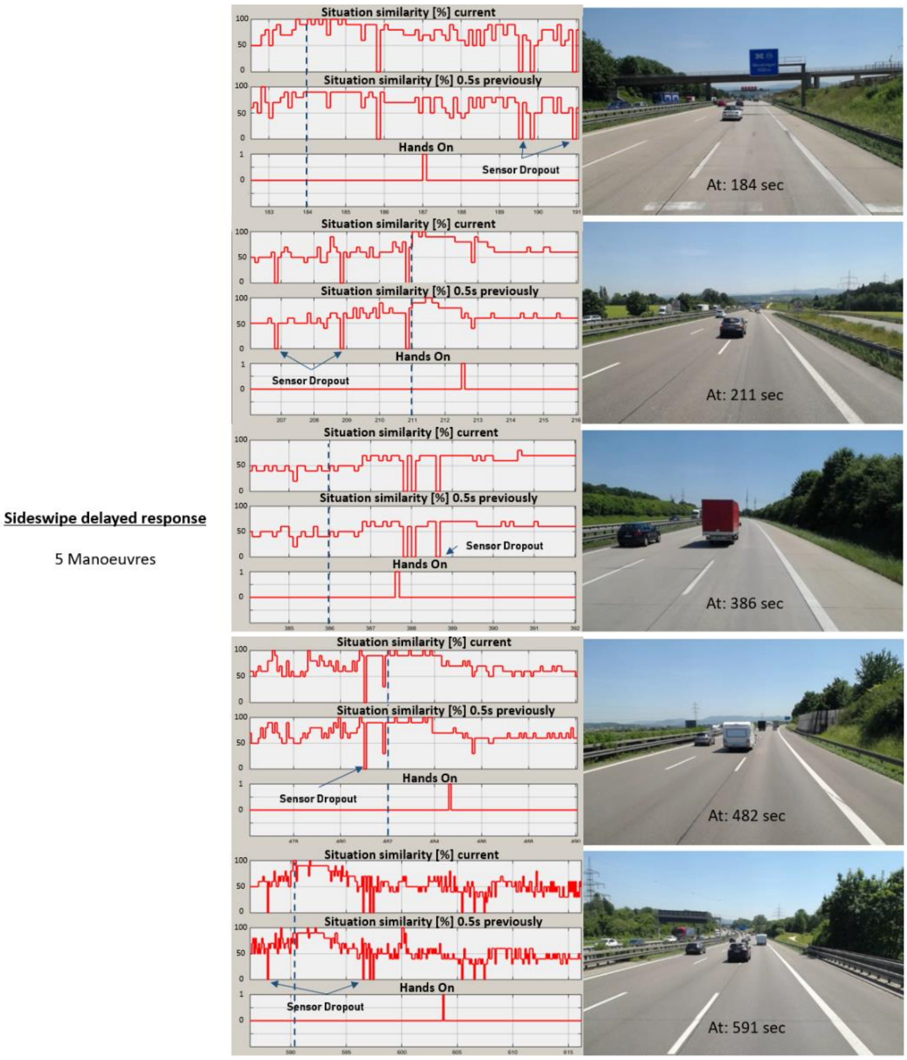


*Figure 12. Five sideswipe manoeuvres with delayed driver response. Trace data depicts confidence values for current and delayed most critical objects in the environment. The hands-on signal generated by the driver is also depicted. The blue line indicates the point in time, to which the video-snapshot corresponds.*

## Conclusion

The introduction of our subjective complexity model is an innovative solution of a learning and adaptive assistance system. By recording driver self-initiated unforced take-overs during automated driving, it is possible to monitor take-overs without interpretation of intent and behaviour. If proven reliable and beneficial, this system can predict preferences in which the driver does not trust the self-driving vehicle or feels the need to manage the driving situation. Trust is an essential component in the human-machine-interaction during automation, as drivers should be able to anticipate system behaviour. If this is not possible, self-initiated take-overs are likely and the model offers assistance. Through continuous learning of relevant situations in which the driver wishes to control the vehicle, the vehicle itself can suggest take-over predictively. This offers different configurations of predictions for different drivers and roads. The functional layout of the model also allows the adjustment of sensors, where the effect on the predictability of take-over can be tested.

Apart from being an adaptive driver assistance system, the model can function as a carrier technology for the investigation of objective and subjective complexity. Thereby, a solution for the second part of our research question is proposed. One of the main obstacles is that sufficient data are difficult to record for this theoretical comparison. On the brink of introducing automated driving to vehicles, previously the driver continuously held control of the vehicle. This made a differentiation difficult between instances, in which the driver considered the environment to be complex. Self-initiated take-overs are valuable for the interpretation of subjective complexity. These situations show that meaning of the temporal and spatial characteristics of surrounding objects from the drivers' perspective was complex enough to motivate a take-over. It should be mentioned that self-initiated take-overs could also occur due to uncritical situations, e.g. terminating automation. In order to truly investigate the differences of subjective and objective complexities, the first part of the research question, a long-term data collection of individual drivers is required that needs documentation of driver intent.

The results of the prediction accuracy of the model shows satisfactory results. While the sideswipe manoeuvres in the test dataset were identified prior to delayed take-over in four of the five instances, one unlearned situation was not identified, see Figure 5. However, there are several reasons and possibilities to improve prediction and the validation of the model. A filtering of the signal is required for subsequent versions to bypass sensor dropout and smooth the prediction value signals. Another shortcoming in our proof of concept are the high number of false positives. It should be investigated whether these false positives occurred, due to the low distinction between a sideswipe manoeuvre being initiated and vehicle continuing in their lane. Furthermore, the point in time in which the driver initiates take-over can vary dramatically, making it difficult for the system to reference the correct critical object to the situation. Reaction times of a driver must possibly be taken into account. Finally, the system can never abstract the data to new situations. Each situation has to have happened similarly in order for the model to predict the situation in the future. However, based on the introduced conformity parameter, see Figure 1, the model can parameterise to achieve different levels of generalisation.

The model shows that this type of assistance system has promising applications in the driving context as well as research. An applied subject complexity assistance would require larger datasets, a higher variance of critical unrequested take-overs as well as seldom occurrences. The model could also be realized with a machine learning approach, however, the presented solution has the added benefit of clearly showing how and why the system functioned with specific predictions. In the future, a large dataset will be utilized as a basis for a parametrization of all variables as well as the expansion of vehicular sensor for further kinematic description of the environment.

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