A Method for the Selection of Challenging Driving Scenarios for Automated Vehicles Based on an Objective Characterization of the Driving Behavior*

Thomas Ponn[1], Alexander Schwab[2], Christian Gnandt[2], Jakub Zahorsky[3] and Frank Diermeyer[1]

Abstract— **The aim of this paper is to present a methodology for the objective characterization of the driving behavior of automated vehicles. By determining the driving behavior, it is possible to adapt future test cases specifically to the capabilities of the system to be tested and thus to identify particularly informative, challenging and therefore potentially critical scenarios. These are of major importance because the safety validation of automated vehicles by using field tests only is no longer economically feasible. Initial results show that the number of relevant scenarios for the evaluation of automated vehicles can be significantly reduced with the developed method, which contributes to overcome this dilemma.**

I. INTRODUCTION

Due to the infinite number of possible traffic scenarios, the evaluation of the safety of automated vehicles (AVs) is complex and time-consuming. Particularly in the homologation of AVs, a minimum number of expressive tests should be selected. One way to reduce the total number of scenarios to be tested is to objectively characterize the driving behavior of AVs. If, for example, the automated driving function generally drives close behind a leading vehicle and brakes late in the event of a vehicle cutting-in in front of the ego-vehicle, then these characteristics should be taken into account when creating challenging scenarios.

In order to efficiently determine the test scenarios for the characterization of driving behavior, a systematic approach will be developed. In addition to technical literature, the basis is also the Driving License Directive and driving safety training courses. For each scenario, Key Performance Indicators (KPIs) are defined for evaluating driving behavior. In addition, the parameters of the scenario to be varied, such as the curve radius, are determined. The scenarios can be carried out using simulations or test site tests. On the basis of the test results, the capabilities of the automated vehicle can be objectively evaluated by the KPIs defined a priori. If KPIs exceed defined values, a behavior characteristic can be automatically deduced and this information can be taken into account in all future test cases.

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This contribution therefore presents a novel approach for an objective driving behavior characterization of AVs, with which relevant and particularly challenging scenarios for the system to be tested can be identified. The overall methodology of the author to identify relevant scenarios for the type approval of automated vehicles is presented in [1]. In addition to the paper presented here, a further part of the overall method is described in [2].

The article is structured as follows: Section II introduces important definitions and previous work in the field of generating challenging scenarios and determining the driving behavior. Section III describes in detail the developed procedure. Section IV shows the results of an exemplary application of the newly developed approach. The results are then critically discussed in Section V. A summary (Section VI) including an outlook for future work concludes the article.

II. RELATED WORK

The following section defines basic vocabulary, gives an overview of current approaches to define challenging test cases for automated vehicles and provides a summary of data sources used in this publication to determine the driving behavior. At the end of this section, the research question is defined.

A. Definitions

Scene and scenario In this paper we use the definition of ULBRICH ET AL. [3] for the terms scene and scenario. According to this definition, a scene describes a snapshot of the environment including all entities. A scenario, on the other hand, is the chronological sequence of several scenes, starting with a start scene.

Furthermore, MENZEL ET AL. [4] divides scenarios into the following three categories:

Functional scenario Functional scenarios represent the first and most abstract level of scenarios. The description of the scenarios is on a linguistic level.

Logical scenario If functional scenarios are described in detail and in the physical state-space, one speaks of logical scenarios. The parameters of logical scenarios can be defined with a five-layer-model from BAGSCHIK ET AL. [5].

Concrete scenario If the parameters of a logical scenario have exactly one fixed value assigned to them, the scenario is concrete.

In addition, we define a test case within the scope of this publication as follows:

Test case A concrete scenario in combination with the evaluation criteria (KPI) for this scenario results in the test case.

Starting from a logical scenario, an infinite number of concrete scenarios can be derived. For the assessment of AVs, particularly critical concrete scenarios are of interest. Based on [1], a distinction is made between challenging and critical scenarios. These two categories are a subset of the relevant scenarios. A graphical explanation is shown in Fig. 1. The area highlighted in light gray thereby represents the infinite number of concrete scenarios that can be derived from a logical scenario.

Relevant scenario All scenarios that contribute to the assessment of AVs and exceed a minimum exposure - which is not yet established - are considered relevant. Relevant scenarios do not have to be very challenging, such as the beginning of a speed limit. This is relevant for certification, as an AV must comply with existing traffic rules. Very simple scenarios can be considered irrelevant, such as driving on a straight highway without surrounding traffic and in good weather conditions.

Challenging scenario The parameters from the five-layer-model [5] can be defined in such a way that the resulting concrete scenario becomes particularly challenging for the System Under Test (SUT). This can be achieved, for example, by defining difficult road geometries, weather conditions or by defining particularly complex trajectories of surrounding traffic participants. Whether a scenario is challenging can be assessed before the test case is executed.

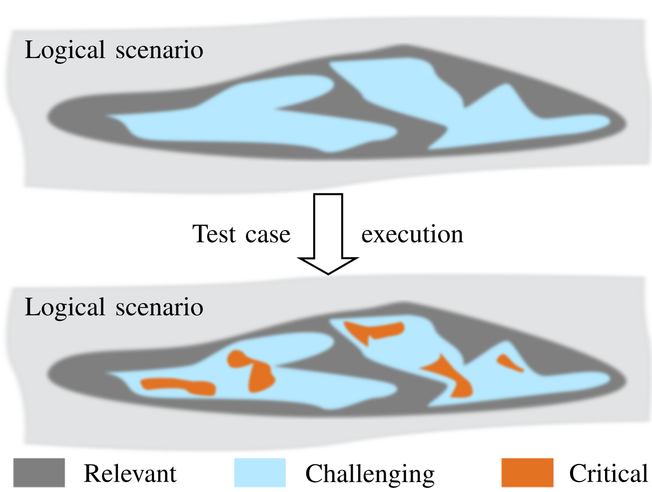


Fig. 1: From one logical scenario an infinite number of concrete scenarios can be derived (light gray area). Sub-sets of the infinite concrete scenarios are relevant, challenging and critical scenarios. Whether a challenging scenario becomes a critical scenario depends on the performance of the system. Defining particularly challenging scenarios increases the probability that a critical scenario will occur.

Critical scenario In this paper, criticality is defined as the proximity to an accident. To measure criticality, we can use indicators such as Time-To-Collision (TTC) [6]. If a very short reaction time of the SUT is required in a scenario (e.g. there is suddenly a stationary object in front of the ego-vehicle), then it can be concluded before the test case is executed that it is a critical scenario. These types of critical scenarios are relatively straightforward to define and therefore not considered further in this publication. Regardless of system performance, the scenario has a certain degree of criticality. Scenarios that start in a non-critical state (i.e. TTC above threshold[1]) and end in a critical state (i.e. TTC below threshold) due to incorrect system decisions in the course of the scenario are more difficult to identify and therefore of great importance in the context of this publication. These are dependent on the performance of the system and can therefore only be detected after or during test case execution.

Consequently, when evaluating AVs, a special focus must be given to those scenarios in which insufficient system performance arises and thus a critical scenario occurs. Since these are difficult to identify a priori, challenging scenarios are defined. Under the assumption that the probability of a critical scenario occurring increases with particularly challenging scenarios, a methodical approach to identify challenging scenarios is important.

B. Approaches to define challenging test cases

One way of selecting challenging scenarios is to use accident databases [8], [9]. However, the current accident databases contain only human-caused accidents, i.e. they are challenging and also critical scenarios for humans. The degree to which these test cases are also challenging for automated vehicles cannot be determined a priori. Nevertheless, these scenarios can be used in the safety argumentation for the potential of accident prevention in current accidents. Further approaches based on real driving data can be found in [10], [11]. Extreme value theory is used to determine the most difficult test cases and their probability of occurrence.

Other approaches are based on the generation of challenging scenarios through simulation executions and optimization using a fitness function [12]–[14]. The fitness function can contain elements such as criticality [13] or special difficulties [15], [16]. For example, Klischat [15] uses the reachable sets [16] of other road users to reduce the drivable area for the SUT. Another approach for defining challenging scenarios is the application of intelligent sampling techniques [17].

In summary, there is a lack of system-specific selection of challenging scenarios. Therefore, the driving behavior of the SUT is included in this publication. The next section shows the basic literature for determining driving behavior.

[1]Based on literature, van der Horst and Hogema [7] define the threshold between uncritical and critical at TTC=1.5 s.

C. Driving behavior

In order to determine the driving behavior of automated vehicles, objective KPIs and characteristic situations in which a characteristic response of the SUT can be clearly observed are required. If one combines the characteristic response and KPI, the driving behavior can be determined automatically and objectively. In the following, existing approaches from literature are shown for both subject areas.

1) Key Performance Indicators (KPIs): Many publications deal with key performance indicators for assessing driving behavior. While some focus exclusively on the human being as the driver of the vehicle [18], others consider the constellation in which the driver is supported by driver assistance systems [19]. HOLZINGER [20], [21] focuses particularly on driver assistance systems in his two publications. HOLZINGER defines KPIs for the automated longitudinal control by an Adaptive Cruise Control (ACC), for the automated lateral control by a Lane Keeping Assist (LKA) and additionally KPIs for the evaluation of an automated lane change.

If very aggressive or defensive behavior is also regarded as driving behavior, then KPIs are also required to determine the driving style [22]–[24]. Frequently used KPIs are longitudinal and lateral acceleration during driving [23], [25]. However, defensive or aggressive driving behavior is strongly dependent on the respective situation, so that the definition of thresholds for the KPIs is carried out situation-specifically [24].

2) Characteristic situations (functional scenarios): Characteristic driving situations can be available in the form of functional (simple, short description of the situation) or logical (description including parameters and their ranges) scenarios. A characteristic driving situation in longitudinal control is, for example, the stopping of the preceding vehicle [21]. Further driving situations can be taken from ERSOY [26, p. 174] and [27], [28].

Not only classical literature, but also other sources such as the (German) Driving License Directive and Driving Safety Trainings are suitable as a database for characteristic situations. The German Driving License Directive [29], together with the Driving License Questionnaire [30] for the theoretical examination, contain, among other things, situations that are unlikely to occur in real traffic but that are important for the basic safe driving of a vehicle. By using simulation, these situations can be verified for AVs. During driving safety training, the behavior of the driver in extreme situations is evaluated. In the case of AVs, this can also be transferred to the simulation and thus the driving behavior of the driving function in particularly critical situations can be evaluated.

D. Research question

An infinite number of scenarios can be defined for the safety assessment of AVs. An exact determination of the safety level of the vehicle is therefore impossible. In order to be able to make a precise statement about the safety of the system with as few test cases as possible, there are already various approaches in the literature to define / identify scenarios that are as challenging and critical as possible. None of the existing approaches includes system-specific driving behavior. Therefore, the following question should be answered in this publication: How can we determine the driving behavior of an AV and then use this information to define system-specific challenging scenarios for the evaluation of the vehicle's safety?

III. METHODOLOGY

This chapter describes the method developed to identify weak points in the driving behavior of an automated vehicle on the basis of a driving behavior characterization and to use this information to design all further vehicle tests to be more challenging and therefore potentially critical.

A. Overall approach

A summary of the methodology can be found in Fig. 2 and is briefly explained below. From the state of the art, specific functional scenarios can be derived that can be used to evaluate driving behavior. Parameters with which the scenario can be described are assigned to these. Thus, the functional scenarios become logical scenarios. All concrete scenarios derived from the identical logical scenario have the same KPIs, which are used to evaluate the result later. Therefore, the corresponding KPIs are already assigned to the logical scenarios. Subsequently, the subdivision into the corresponding application purpose takes place based on the

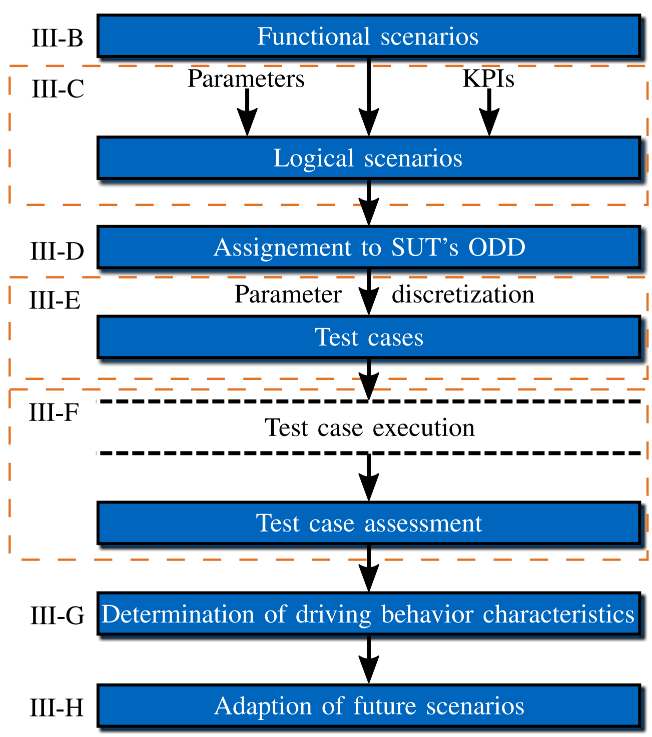


Fig. 2: Overview of the methodology developed. On the left side you can see the sections explaining the corresponding step of the procedure in detail. In addition, a summary of the overall concept can be found in Section III-A.

Operational Design Domain (ODD) of the vehicle to be tested. By varying the parameters, concrete scenarios are obtained which, together with the KPIs, represent the test cases. The results from simulation and / or test site tests are then evaluated using the KPIs. Based on the KPI values, weak spots in the driving behavior of the vehicle are identified. These can be taken into account when defining future concrete scenarios and thus contribute to the identification of system-specific challenging test cases for the SUT. The following sections describe the individual steps in detail.

B. Functional scenarios

Technical literature, the Driving License Directive and scenarios from driving safety training courses are used to define the functional scenarios. In order to get more structure into the concept, the scenarios are differentiated into lateral and longitudinal control according to the distinction frequently used in vehicle dynamics. The primary driving task within the scenario is decisive for the classification. For example, the speed (longitudinal control) can vary during an overtaking maneuver, but the primary driving task is to change the lane twice. Therefore, the overtaking maneuver is assigned to lateral control. In addition, the scenarios are classified according to which acceleration occurs primarily during the scenario. A periodic, a transient, a constant or no acceleration can occur. When driving through a curve, for example, a constant lateral acceleration is to be assumed, which is why the scenario "driving through a curve" is to be assigned to lateral control with constant acceleration. Table I summarizes the classification applied.

C. Adding parameters and KPIs

To define logical scenarios, parameters and their ranges must be assigned to the functional scenarios of Section III-B. To perform this task in a structured way, the five-layer model of BAGSCHIK [5] (see Section II-A) is used. Various parameters are relevant for the individual functional scenarios. In addition, the required range of a parameter can vary from scenario to scenario. Since the relevant parameters in the scenarios are different, default values are defined for each parameter. This means that if a parameter is not specified for a scenario, it assumes the default value. An example is the scenario "driving through a curve" in which, among other parameters, the desired speed and the curve radius are defined with corresponding ranges. The longitudinal and lateral gradients of the road are irrelevant in this scenario, which is why they are not explicitly defined and therefore assume the default value. In our example, the default value for these two parameters is zero. A total of 34 parameters are defined for the description of all functional scenarios from Section III-B.

The KPIs are assigned to the logical scenarios because each concrete scenario derived from the same logical scenario is evaluated against the same KPIs. The KPIs are based on physical measures and are divided into six groups. Table II gives an overview of the groups, the number of KPIs within each group and a KPI as an example.

TABLE I: Distinction of the scenarios into longitudinal and lateral control. Further subdivision according to the primary acceleration type occurring during the scenario. A distinction is made between no, a constant, a transient and a periodic acceleration. The table shows the number of identified scenarios for each category. A description of all scenarios can be found in [31].

	Number of scenarios			
	Null	Constant	Transient	Periodical
Longitudinal	18	29	5	1
Lateral	0	9	13	2

TABLE II: The KPIs are divided into six groups according to the corresponding physical quantities. The table shows the number of defined KPIs per category and one corresponding KPI as an example.

Based on	Number of KPIs	Example
Distance	6	Distance to center of ego lane
Velocity	2	Maximum lateral velocity
Acceleration	10	Maximum lateral acceleration
Angle	3	Yaw angle
Time	3	Time-To-Collision (TTC)
Frequency	2	Oscillation around the center of the lane

D. Assignment to SUT's ODD

Systems with automation level 3 or 4 (according to [32]) have a limited ODD within the operation of the system is intended. The defined scenarios from Section III-B are assigned to the ODDs city center, country road and highway. Scenarios that do not address a specific ODD are assigned to the "general" category. In addition, individual scenarios can also be assigned to two ODDs. Table III shows the number of scenarios per category.

E. Test cases

After the relevant logical scenarios have been reduced using the ODD of the SUT, the concrete scenarios or, in combination with the KPIs, the test cases can be determined using a parameter variation. All relevant parameters are discretized for this purpose. There are parameters, such as the value of the speed limit, which already exist in discrete form. All other parameters can have any value within their range

TABLE III: The defined scenarios are subdivided according to four different Operational Design Domains (ODD). The table shows the number of scenarios per category.

Operational Design Domain (ODD)			
General	City center	Country road	Highway
38	26	3	10

and must therefore be discretized. A compromise between fine and rough discretization must be found when selecting the discretization steps. A rough discretization leads to a small number of test cases, which is positive in terms of cost and time. However, if the number of scenarios is too small, it is no longer possible to determine whether it is a general driving characteristic of the SUT or a unique event. A very fine discretization, on the other hand, leads to general statements about the driving behavior of the SUT, but the number of concrete scenarios n_{cs} increases drastically with the discrete values per parameter n_{dv} (see Equation 1).

$$n_{\text{cs}} = \prod_{i=1}^{N} n_{\text{dv},i} \tag{1}$$

The number of parameters in Equation 1 is depicted as N.

F. Test case execution and assessment

The execution of the defined test cases can be carried out with the aid of simulations or on the proving ground. Due to the high cost and time involved in test site testing, more and more simulations are being used. To use the simulation, the concrete scenarios defined in Section III-E are converted into the corresponding format of the simulation program. Often the combination of OpenDRIVE and OpenSCENARIO is used. In OpenDRIVE, the road network (road level, traffic infrastructure, temporary manipulation of the first two layers) is defined, which corresponds to the first three layers of BAGSCHIK's five-layer model. OpenSCENARIO represents layers 4 and 5 with moving objects and environmental conditions. Subsequently, the simulation of the concrete scenario can be executed in the simulation environment. The creation and validation of the required models for vehicle, environment, traffic and driver are not part of the presented methodology and are assumed to be given. The test case execution returns the trajectory of the SUT as output. Together with information already defined a priori, such as the trajectories of the surrounding traffic, the scenario-specific KPIs can be calculated and compared with maximum acceptable values or reference values from literature, norms and standards.

G. Determination of driving behavior characteristics

Once all KPIs have been determined, characteristics of the system can be determined. Some characteristics can be used to reveal and address weaknesses in the driving behavior of the SUT. The definition of characteristics is based on expert knowledge and is done manually. This is commonly carried out according to the procedure: If a KPI exceeds a limit value or is within a certain range, this characteristic occurs. A combination of several KPIs is also possible. By using different parameter variations, it can be ensured that this is actually a characteristic of the driving behavior of the SUT and not a randomly discovered single event.

H. Adaption of future scenarios

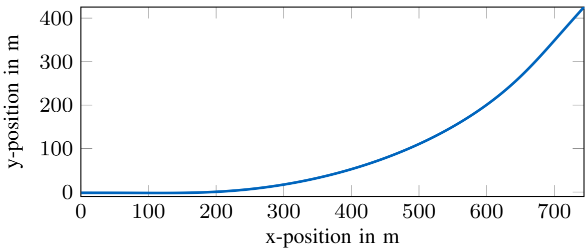
The aim of the methodology presented is to increase the efficiency in defining challenging scenarios for testing AVs. The characteristics derived from expert knowledge in Section III-G are automatically taken into account in the definition of further scenarios. For example, an SUT can always initiate the overtaking process at a similar TTC or a similar distance to the front vehicle. This TTC value is therefore a characteristic value for this system. This information can be used to specifically test the behavior of the SUT in all subsequent scenarios with surrounding traffic in which a lane change can just (or no longer) be performed at the characteristic TTC or distance.

IV. RESULTS

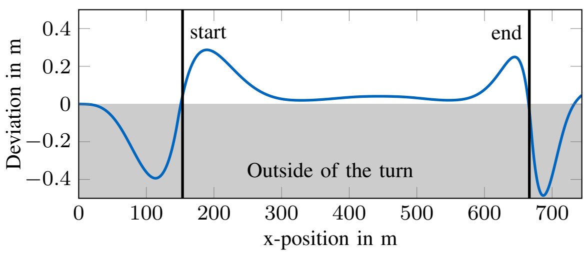
This chapter presents exemplary generated results. Here, the scenario "driving through a curve" is described in detail and the procedure is presented step by step. It is examined whether the automated vehicle shows characteristic behavior when driving through a curve. The focus is on lateral control with transient acceleration (see Table I) during entering and exiting the curve. The simulations were performed with the commercial simulation tool IPG CarMaker®. A simple dummy function for lateral control was used as a driving function. Table IV shows an overview of the considered scenario, the parameters and the used KPI. The ranges for the curve radii and the velocities are in accordance with category EKL 2 of the German guideline for the construction of country roads [33]. For simplicity, the clothoid parameter is not considered. The width of the vehicle w_{veh} as well as the width of the lane w_{lane} are chosen as default values which are $w_{\text{veh}} = 1.82\,\text{m}$ and $w_{\text{lane}} = 3.50\,\text{m}$, respectively. As KPI, the deviation from the center of the lane is considered and not, for example, the distance to the boundary of the lane, because the former can be used to compare the behavior at different lane widths. On motorways in Germany, lanes with widths of $3.25\,\text{m}$, $3.50\,\text{m}$ or $3.75\,\text{m}$ can normally occur (without construction sites), which results in a different distance to the lane boundary with identical driving behavior.

TABLE IV: Overview of the scenario "driving through a curve".

Section	Name of step	Description
III-B	Functional scenario	Driving through a curve
III-C	Parameters	Curve radius R Desired velocity v_{set} Direction of curve $c_{\text{direction}}$
III-C	Parameter ranges	$R \in [400, 1000]$ in m $v_{\text{set}} \in [60, 100]$ in $\text{km}\,\text{h}^{-1}$ $c_{\text{direction}}$ $\{left, right\}$
III-C	KPI	Deviation from the center of the lane in m
III-D	SUT's ODD	Country road
III-E	Parameter discretization	R in $200\,\text{m}$ steps v_{set} in $20\,\text{km}\,\text{h}^{-1}$ steps
III-F	Test case execution	IPG CarMaker

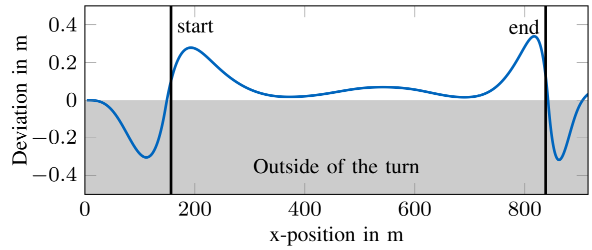


(a) Course of the left turn

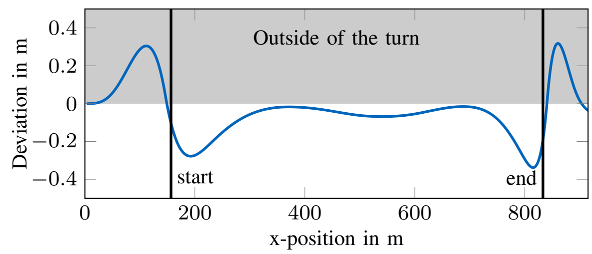


(b) Deviation of the center point of the vehicle to the center line of the ego-lane. If the vehicle drives more left in its own lane, i.e. closer to the center line of the road, the deviation is positive. For the left-hand curve under consideration, a negative deviation thus means a deviation towards the outside of the curve. The black vertical lines represent the beginning and the end of the curve respectively.

Fig. 3: The course of the curve and the deviation from the center of the lane for a left curve with radius $R = 600\,\mathrm{m}$ at a desired velocity of $v_{\text{set}} = 90\,\mathrm{km\,h^{-1}}$.



(a) Left turn



(b) Right turn

Fig. 4: Comparison of the system behavior between a left and a right curve with an identical radius of $R = 800\,\mathrm{m}$ at identical speed of $v_{\text{set}} = 70\,\mathrm{km\,h^{-1}}$. The system shows the same driving behavior, a clearly visible curve cutting, in both left and right-hand curves. Due to the comparable behavior, only the left-hand curve will be considered in the following. The black vertical lines represent the beginning and the end of the curve respectively.

Test case assessment: The evaluation of the simulated test cases is based on the predefined KPI. In the example under consideration, this is the deviation of the vehicle's center point from the center line of the ego-lane. If the vehicle drives exactly in the middle of its own lane, the deviation is zero. If the vehicle drives more left in its own lane, i.e. closer to the center line of the road, the deviation is positive. The deviation is negative if the vehicle drives more on the right side of its own lane, i.e. closer to the outside of the road. Fig. 3 shows the course of the curve and the deviation from the lane center line for a left curve with radius $R = 600\,\mathrm{m}$ at a desired velocity of $v_{\text{set}} = 90\,\mathrm{km\,h^{-1}}$.

Derivation of driving behavior characteristics: The exemplary results in Fig. 3 show by means of the exemplary driving function that the vehicle drives to the outside of the curve before entering a left-hand corner and then in the further course it clearly cuts the curve. This is a single observation that has to be checked for the overall operating area. If the observation occurs in a large number of concrete scenarios, one can consider a characteristic in the driving behavior of the AV. For the example given here, the parameters direction of curve $c_{\text{direction}}$, curve radius R and velocity v_{set} are used to determine whether a characteristic behavior is involved. Fig. 4 compares a left and a right turn with identical radius R and velocity v_{set}.

Since there is no significant difference between left and right curves, it must still be checked whether the observed behavior also occurs over the entire operating range of curve radius and speed. In Fig. 5, the maximum deviation from the lane center line towards the inside of the turn at the curve entrance of a left turn is plotted over the whole range of the two parameters. In the left-hand curve, we look at the peak at the curve entrance towards the inside of the curve, because in right-hand traffic this is the side of the oncoming traffic and therefore the potential for critical situations is the highest. For right-hand curves, the peak before the curve entrance towards the outside of the curve is of particular importance. Analogously, this applies to the behavior at the curve exit.

Adaption of future scenarios: Since challenging test cases with particularly high significance are required for the evaluation and especially for the certification of AVs, the characteristics discovered can be included in the definition of further challenging test cases for the system to be tested. For the considered SUT, obstacles and objects shortly after entering the curve are particularly challenging on the inside of the curve and this can be explicitly taken into account with the help of the methodology presented. A further advantage is the reduction of possible parameter variations, because the position of the object can be optimally determined for all other curve scenarios. Assuming ten discrete positions of an object, the number of possible parameter combinations for concrete scenarios can be reduced to $10\,\%$ of the initial value according to Equation 1, because this parameter no longer needs to be varied.

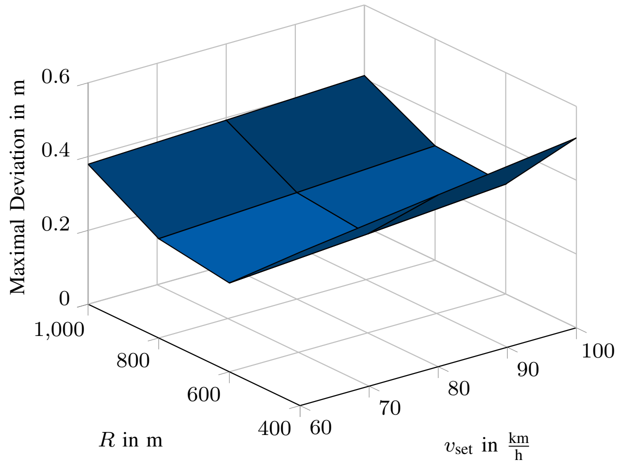


Fig. 5: Maximal deviation of the center point of the vehicle to the center line of the ego-lane shortly after the entrance of a left turn. The SUT shows an identical performance over the entire speed range and over all curve radii. In all concrete scenarios, there is a positive deviation, i.e. the SUT drives much closer to the inside of the curve in all tested left-hand curves shortly after the curve entrance.

V. DISCUSSION

The procedure was implemented as a prototype, tested on the basis of exemplary scenarios and the functionality was confirmed on the basis of these scenarios. However, a complete characterization of the driving behavior has not yet been carried out. Following a complete characterization, an evaluation of the defined scenarios can be carried out as to which of these have a strong significance. In the future, it will be possible to focus on these scenarios and thus make the procedure more efficient.

The developed methodology has the limitation that a successful application cannot be guaranteed for all vehicles. This can occur if the vehicle to be tested does not show any noticeable behavior. If, however, the vehicle shows certain characteristics, the approach presented here can make a valuable contribution to finding challenging test cases efficiently. Even if no noticeable characteristics are detected, the procedure presented can generate additional value for the market launch of automated vehicles. Due to the use of driving situations from the theoretical driving test, an increase in acceptance in society can be expected if mastered successfully.

VI. CONCLUSION

This contribution addresses a novel method for identifying system-specific challenging and therefore potentially critical scenarios for the safety assessment of automated vehicles. This is achieved by the developed method, which takes characteristics of the driving behavior of the vehicle under test into account for the definition of future test cases. For this purpose, relevant parameters, their ranges and key performance indicators required for the evaluation of the scenarios are defined on the basis of functional scenarios. After selecting the scenarios according to the operational design domain of the automated vehicle, continuous parameters are discretized and concrete scenarios are generated by parameter variation. After the tests have been performed and evaluated using the defined key performance indicators, the characteristic driving behavior of the system can be derived. An example of this is the distance or time interval at which the ego-vehicle begins to overtake a slow-moving vehicle or at which side distance objects are overtaken. Based on this information, all future test cases can be adapted so that the defined scenarios represent the highest possible challenge for the system. While this publication focused on the development of the methodology and the prototypical application, the driving behavior characterization will have to be carried out in detail in future work.

ACKNOWLEDGMENT AND CONTRIBUTIONS

Thomas Ponn (corresponding author) initiated and wrote this paper. He was involved in all stages of development and primarily developed the research question as well as the overall concept. Alexander Schwab wrote his master thesis on the presented topic and developed parts of the concept during his thesis. Christian Gnandt provided essential scientific background information regarding the safety assessment of Advanced Driver Assistance Systems and Automated Driving. Jakub Zahorsky conducted the simulations and Frank Diermeyer contributed to the conception of the research project and revised the paper critically for important intellectual content. He gave final approval of the version to be published and agrees to all aspects of the work. As a guarantor, he accepts responsibility for the overall integrity of the paper.

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