A METHOD FOR SCENARIO RISK QUANTIFICATION FOR AUTOMATED DRIVING SYSTEMS

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Paper Number 19-0129

ABSTRACT

Recent innovations, such as automated driving and smart mobility, have elevated the safety-criticality of automotive systems due to the impact of these technologies on the traffic behavior and safety. New safety validation and assessment methodologies are required to provide the level of assurance that matches the societal impact of these systems. The objective of this paper is to introduce a novel method for assessment and quantification of the risk of a driving scenario considering the operational design domain. For our proposed method, we assume that a scenario consists of activities (performed by different actors) and environmental conditions that leads to a potentially hazardous consequence. The risk of a driving scenario is the product of the probability of the exposure of a scenario and the severity of the hazardous consequence of that scenario. We introduce a systematic method for calculating the probability of exposure, where we assume a causal relation between the activities that constitute a scenario. By making educated assumptions on the dependencies among the different activities and environmental conditions, we simplify the calculation of the probability of the exposure. For estimating the severity, we employ Monte Carlo simulations. We illustrate the use of our proposed method by applying it to an example of a collision avoidance system in a cut-in scenario. We use naturalistic driving data acquired from field studies on the Dutch highways to determine the risk. The presented example illustrates the potential of our proposed risk estimation method. Using our proposed method, we can compare the safety criticality of various scenarios in a quantitative manner, which can be used as a safety metric for evaluating automated driving systems. This can lead to stronger justification for design decisions and test coverage for developing automated vehicle functionalities.

INTRODUCTION

New developments in the automotive industry towards higher levels of automation are introducing new safety concerns for vehicles. Test procedures and performance measures need to be adapted for evaluation of vehicles with an Automated Driving (AD) system. The safety and reliability of the AD vehicles must be validated in principle for all possible traffic situations that an AD system may encounter on the road, before these systems can be taken into production.

Scenario-based safety validation for automated driving is one of the proposed approaches that is broadly supported by the automotive community. This is reflected in the ISO/PAS 21448:2019 standard on the safety of th intended functionality (SOTIF) [1]. Related projects in Germany (Pegasus [2]), The Netherlands (StreetWise [3]), and Singapore [4] strongly support this approach. Risk assessment is an essential component of the safety validation as it indicates the acceptance criteria of the AD system.

The ISO 26262:2018 [5] captures the state of the art in automotive functional safety. It defines the safety lifecycle and the related safety activities such as Hazard Analysis and Risk Assessment. Other methodologies, such as STPA [6], give guidelines on safety engineering based on systems theory. From the mentioned sources, the only one that offers a framework for measuring risk is ISO 26262. It defines risk as:

Definition 1 (Risk [5]) *The combination of the probability of occurrence of harm and the severity of that harm.*

ISO 26262:2018 gives guidelines to assess risk based on vehicle level hazardous events. A hazardous event is the combination of a vehicle level hazard with operational situation or scenario. It requires analyzing each hazardous event risk individually based on three parameters of Severity, Probability of exposure, and Comparability. The combination of these parameters contributes to constructing the Automotive Safety Integrity Level (ASIL). In this framework, each parameter is quantified in three or four levels that construct the ASIL ranking A, B, C, D, and QM, where ASIL A represents the least critical level and in ascending order, ASIL D the most critical level. Quality Management (QM) means that the identified hazard is not critical enough for the safety processes, and the quality management system of the manufacturer should suffice for reducing the risk. We depict the ASIL ranking graph in Figure 1.

The ASIL methodology for risk assessment relies on the experts' judgments of the three risk parameters. The ISO 26262:2018 provides some general guidelines for assessing these parameters. However, the assessment is for the most part subjective and dependent on the experts who carry it out. Moreover, it is only capable of evaluating the risk of a single (hazardous) event within the context of a generic operational situation.

The alternative methodology proposed in STPA has the means for providing a quantitative risk assessment as it provides the means for connecting the hazard identification to a control system and its characteristics. However, this method skips the risk assessment entirely and does not offer any solutions.

We argue that as the automotive systems move towards higher automation levels, we require more formal methods for risk assessment. By quantifying risk assessment, we reduce the risk of subjective errors in the judgment. Risk quantification is a step towards run-time risk assessment for the autonomous systems.

The objective of this paper is to introduce a method for assessment and quantification of the risk of a driving scenario taking into account the entire operational situations and their relations. This is achieved by calculating the

Controllability C	Probability of Exposure (E)	Severity (S)			
		S0	S1	S2	S3
C1	E1	QM	QM	QM	QM
	E2	QM	QM	QM	QM
	E3	QM	QM	QM	A
	E4	QM	QM	A	B
C2	E1	QM	QM	QM	QM
	E2	QM	QM	QM	A
	E3	QM	QM	A	B
	E4	QM	A	B	C
C3	E1	QM	QM	QM	A
	E2	QM	QM	A	B
	E3	QM	A	B	C
	E4	QM	B	C	D

Figure 1: ASIL risk assessment graph.

Table 1: The terms and definitions.

Term	Definition
Severity	An estimate of the extent of harm to one or more individuals that can occur in a potentially hazardous event [5]
Exposure	The state of being in a driving scenario
Risk	The combination of the probability of occurrence of harm and the severity of that harm [5]
Condition	The constant parameters describing the environmental aspects of the operational design domain[1]
Actor	An element of a scenario acting on its own behalf [8]
Scenario	A quantitative description of the activities of the ego vehicle and other actors and the conditions from the static environment

probability of exposure to a certain scenario through analysis of real-world driving data. Next, we employ simulations to estimate the severity of the potential hazardous consequence of a scenario.

The paper is structured as follows. We first present the proposed method for estimating the risk quantitatively. Next, we perform a case study to illustrate the method using real-world data. We end the paper with a discussion and a conclusion.

PROPOSED RISK ESTIMATION METHOD

In the Hazard Analysis and Risk Assessment (HARA) required by the ISO 26262 standard, the estimation of Automotive Safety Integrity Level (ASIL) is calculated based on a so-called single specific hazardous event [5]. Although the operational situation in which this single event occurs as well as the operating mode are considered in the analysis, still the proceeding and successive events are not taken into account. In this paper, we propose a new method to estimate the risk of a certain scenario considering the whole chain of activities and conditions that constitute the scenario. The estimated risk is based on real-world driving data. To estimate the risk, we quantify the exposure and the severity. In Table 1, we present the definitions of the terms that are used in our proposed methodology.

As explained in Table 1, a scenario consist of a set of conditions and activities, denoted by A and C, respectively. We formulate the exposure as the average number of occurrences of the activities A under the conditions C, denoted by $\lambda_{A,C}$. The severity is the likelihood of the potential hazardous consequence R given the activities A and the conditions C, denoted by the conditional probability $P(R|A,C)$. The risk is computed as the multiplication of the exposure and the severity.

The proposed method is summarized in Figure 2. To compute the exposure, we calculate the likelihood of the conditions, denoted by $P(C)$, and the conditional likelihood of the activities, denoted by $P(A|C)$, based on real-world driving data. This is explained in detail in the next section. For the estimation of the severity, we consider all possible scenarios that are subject to a set of conditions C and consist of the activities A. Therefore, we parametrize the scenarios using the parameter vector θ. Based on the real-world driving data, the probability density function of the parameters, denoted by $P(\theta|A,C)$, is estimated. Next, using simulations, we estimate $P(R|\theta,A,C)$, the likelihood of a potential hazardous consequence R given a parametrized scenario. The details of the estimation of the severity are presented after the details of the estimation of the exposure. Finally, we describe how the risk is estimated based on the estimated exposure and severity.

Calculate exposure

The scenarios are subject to n_C conditions, denoted by $C_1,\ldots,C_{n_C}$. For the sake of brevity, all conditions together are denoted by C, i.e., $P(C_1,\ldots,C_{n_C}) = P(C)$. Many of these conditions might be based on the operational design domain of the AD system and might include conditions with respect to the infrastructure, weather conditions, lighting conditions, and geographical locations.

The first step is to compute the joint probability of the conditions, i.e., $P(C)$. In case these conditions are independent, the probability can be computed by simply multiplying the individual likelihoods for each condition, i.e.,

[1]The operational design domain refers to the "operating conditions under which a given driving automation system or feature thereof is specifically designed to function" [7].

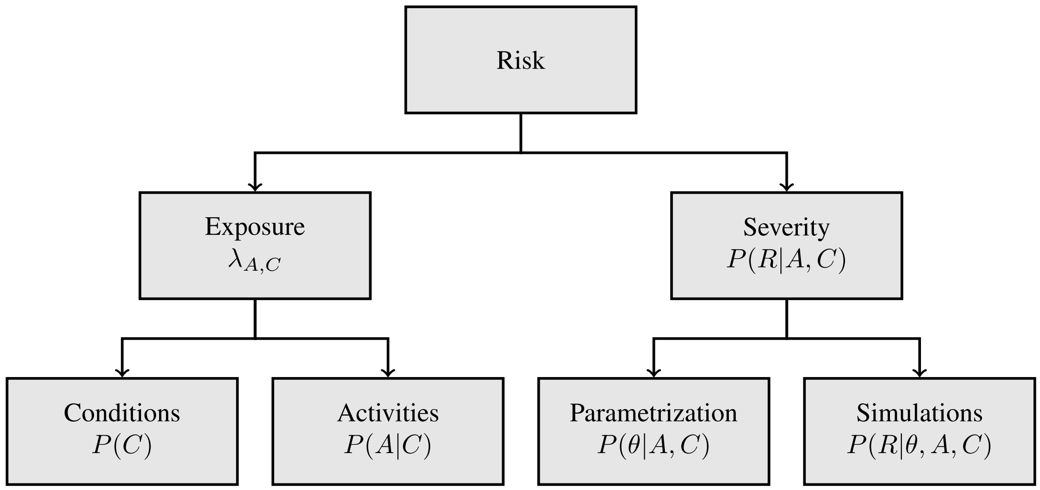

Figure 2: Proposed method for quantifying the risk. The risk is a multiplication of the exposure and the severity.

$P(C) = P(C_1) \cdot \ldots \cdot P(C_{n_C})$. This, however, might not necessarily be the case, which requires either to compute the joint probability or to compute conditional probabilities. In some cases, it might also be reasonable to simply assume that the likelihood of certain conditions are independent.

Note that the the defined conditions might not be the same as the conditions under which the data is collected that is used to compute $P(C)$. This might require additional assumptions, see our case study for examples.

To calculate the exposure, the average number of occurrences of the activities that constitute the scenarios within a certain time interval need to be estimated. Let n_A denote the number of activities, such that $A_1, \ldots, A_{n_A}$ denote the activities. For the sake of brevity, all activities together are denoted by A.

Without loss of generality, we assume that the time interval is an hour. To estimate the number occurrences of the activities, the data for which the conditions C are satisfied are analyzed. The average number of occurrences of the activities A for each hour of driving for which the conditions C are satisfied is denoted by $\lambda_{A|C}$. Next, we can calculate the average number of occurrences of the activities A under the conditions C for each hour of driving:

$$\lambda_{A,C} = \lambda_{A|C} \cdot P(C). \tag{1}$$

Regarding the scenarios consisting of conditions C and activities A, we assume the following:

- The occurrence of one scenario consisting of activities A and conditions C does not affect the probability that a second scenario consisting of activities A and conditions C occurs.
- The rate at which a scenario consisting of activities A and conditions C occurs is constant. I.e., $\lambda_{A,C}$ is constant.
- Two scenarios consisting of activities A and conditions C cannot occur at exactly the same time instant.

Based on these assumptions, the number of occurrences of scenarios consisting of activities A and conditions C is distributed according to the Poisson distribution:

$$P(k \text{ times } A, C \text{ in an hour}) = \exp\{-\lambda_{A,C}\} \frac{\lambda_{A,C}^k}{k!}. \tag{2}$$

Severity

The first step towards estimating the severity is to parametrize the scenarios with a parameter vector $\theta \in \mathbb{R}^d$. The parametrization enables the generation of infinitely many unique individual test cases that resemble the scenarios found in naturalistic driving [3], [9].

In case the parameters are dependent, which is often the case, it is important that the number of parameters is limited to avoid the curse of dimensionality [10]. This often requires some assumptions. An example is presented in our case study in the next section.

To estimate the probability density function (pdf) of the parameter vector θ, i.e., $P(\theta|A,C)$, either parametric models, non-parametric models, or a combination of the two can be used. In case of parametric models, a certain functional form of the pdf is assumed. For example, it might be assumed that the pdf can be modeled using a Gaussian distribution. In this paper, we present a non-parametric approach using Kernel Density Estimation (KDE) [11], [12]. Using KDE, there is no assumption on the functional form of the pdf because the shape of the pdf is automatically computed. With KDE, the estimated pdf is given by

$$P(\theta|A,C) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{\theta - \theta_i}{h}\right). \tag{3}$$

Here, $K(\cdot)$ is an appropriate kernel function and h denotes the bandwidth. From the data, n scenarios are extracted and each scenario is parametrized with θ_i. The choice of the kernel $K(\cdot)$ is not as important as the choice of the bandwidth h [13]. Often, a Gaussian kernel is used, which is given by

$$K(u) = \frac{1}{(2\pi)^{d/2}} \exp\left\{-\frac{1}{2}\|u\|^2\right\}, \tag{4}$$

where $\|u\|^2$ denotes the squared 2-norm of u, i.e., $u^T u$.

The bandwidth h controls the amount of smoothing. For the kernel of Eq. (4), the same amount of smoothing is applied in every direction, although this can easily be extended to a multi-dimensional bandwidth, see, e.g., [14], [15]. There are many different ways of estimating the bandwidth, ranging from simple reference rules like, e.g., Scott's rule of thumb [10] or Silverman's rule of thumb [16] to more elaborate methods; see [13], [17]–[19] for reviews of different bandwidth selection methods.

Let R denote a potential hazardous consequence of a scenario. We define the severity of a scenario with activities A and conditions C as the probability of R, given the activities A and C, i.e., $P(R|A,C)$. We cannot evaluate $P(R|A,C)$ directly, because the outcome of a scenario highly depends on the parametrization θ. Therefore, we estimate $P(R|\theta,A,C)$ through a simulation of the scenario with parameters θ. Using $P(\theta|A,C)$ from Eq. (3), we can compute

$$P(R,\theta|A,C) = P(R|\theta,A,C) \cdot P(\theta|A,C). \tag{5}$$

To obtain $P(R|A,C)$, we need to integrate Eq. (5) over θ, i.e.,

$$P(R|A,C) = \int_{\mathbb{R}^d} P(R|\theta,A,C) \cdot P(\theta|A,C)\,\mathrm{d}\theta. \tag{6}$$

One approach to evaluate the integral of Eq. (6) is to perform Monte Carlo simulations. For sufficiently large N, we have

$$P(R|A,C) \approx \frac{1}{N} \sum_{k=1}^{N} P(R|\theta_k,A,C),\ \theta_k \sim P(\theta|A,C). \tag{7}$$

To improve the accuracy of Eq. (7), importance sampling can be used where the parameters θ are drawn from another distribution with a focus on the critical scenarios, see, e.g., [9].

Calculating the risk

Analogous to the exposure, we define the risk as the number of occurrences of the hazardous consequence R in a scenario consisting of activities A and conditions C in a certain time interval. Let λ denote the average number of these occurrences in an hour of driving. The chain rule of probability tells us that this equals the product of $\lambda_{A,C}$ (i.e., the exposure) and $P(R|A,C)$ (i.e., the severity):

$$\lambda = \lambda_{A,C} \cdot P(R|A,C) \tag{8}$$

Analogous to the number of occurrences of a scenario consisting of activities A and conditions C, we assume that the number of occurrences of a harmful outcome R in a scenario consisting of activities A and conditions C can be modeled using a Poisson distribution:

$$P(k \text{ times } R, A, C \text{ in an hour}) = \exp\{-\lambda\} \frac{\lambda^k}{k!}. \tag{9}$$

Using Eq. (9), to calculate the probability of not having the harmful outcome R in a scenario consisting of activities A and conditions C we simply need to use $k = 0$:

$$P(\text{no } R, A, C \text{ in one hour}) = \exp\left\{-\lambda\right\}. \tag{10}$$

CASE STUDY

In this section, we present a case study to illustrate the method of quantifying the risk for a cut-in scenario. We will first describe the cut-in scenario and the use case. The actual system for which the risk is computed is presented in next. After these two steps, we will go through the steps of our proposed method.

The cut-in scenario and the use case

We want to quantify the risk for cut-in scenarios that are linguistically described as follows: while the ego vehicle drives at a moderate to high speed while staying in its lane, another vehicle cuts into the lane of the ego vehicle, such that this vehicle becomes the ego vehicle's lead vehicle. Furthermore, the ego vehicle needs to brake to prevent a collision.

For the quantification of the risk, 60 hours of data (see also [9]) are collected by driving a specific route in and between Eindhoven and Helmond, The Netherlands, with twenty different drivers, each driving the route twice. Therefore, it is assumed that the use case of the AD system is driving this route. We will use the data for the estimation of the risk. Hence, we will make use of the following assumption:

Assumption 1 *The recorded naturalistic driving data is representative for what a vehicle with the AD system might encounter along the same route.*

System-under-test

To reduce efforts for the assessment, often simulations are employed. However, even simulations can consume considerable time, as these simulations might run real-time [20] or slower when a higher level of detail is used [21]. For our method, we will simplify the simulations, such that the total required time on a common computer is in the order of minutes. Since we are interested in approximate results, a high level of detail is not required.

To simplify the system-under-test, it is assumed that the system's desired acceleration is similar to the adaptive cruise control defined in [9], i.e.,

$$u(t) = k_{\mathrm{d}}(v(t))(d(t) - \tau_{\mathrm{h}}v(t) - s_0) + k_{\mathrm{v}}\left(\dot{d}(t) - ha(t)\right), \tag{11}$$

with

$$k_{\mathrm{d}}(v(t)) = k_{\mathrm{d1}} + (k_{\mathrm{d2}} - k_{\mathrm{d1}})\exp\left\{-\frac{v(t)^2}{2\sigma_{\mathrm{d}}}\right\}. \tag{12}$$

Here, v is the speed of the ego vehicle, d denotes the clearance between the ego vehicle and its predecessor, i.e., the vehicle that performs the cut-in. The relative speed is denoted by $\dot{d}$ and a refers to the acceleration of the ego vehicle. The ego vehicle is modeled using a first order model with a time delay, i.e.,

$$\tau\dot{a}(t) + a(t) = u(t - \theta). \tag{13}$$

Furthermore, the deceleration is limited at $-6\,\mathrm{ms}^{-2}$. A description of the constants of Eqs. (11) to (13) are listed in Table 2. The controller runs at 100 Hz.

Note that there is no intervention of a human:

Assumption 2 *The ego vehicle is fully controlled by the automation system as defined by Eqs.* (11) *and* (12)*. Hence, there is no intervention of a human.*

Table 2: The constants used for the simple automation system of Eqs. (11) to (13).

Parameter	Description	Value
τ_{h}	Desired headway time	$2.0\,\mathrm{s}$
s_0	Safety distance	$1.5\,\mathrm{m}$
k_{d1}	Distance gain at high speed	$0.7\,\mathrm{s}^{-2}$
k_{d2}	Distance gain at low speed	$2.0\,\mathrm{s}^{-2}$
σ_{d}	Shaping coefficient of distance gain	$5\,\mathrm{ms}^{-1}$
k_{v}	Speed difference gain	$0.35\,\mathrm{s}^{-1}$
τ	Time constant of the vehicle model	$0.1\,\mathrm{s}$
θ	Delay of the vehicle response	$0.2\,\mathrm{s}$

Calculate exposure

The cut-in scenarios are subject to the following conditions:

- C_1: The speed of the ego vehicle is within the range of 60 km/h and 130 km/h.
- C_2: There are no restrictions on the weather conditions.
- C_3: There are no restrictions on the lighting conditions.

Obviously, because there are no restrictions to the weather and lighting conditions, we have $P(C_2, C_3) = 1$. For the first condition, we can use the data to estimate the likelihood. The data, however, has been recorded during sunny weather at daylight. Therefore, we need to following assumption.

Assumption 3 *Let C_2' and C_3' denote the conditions of having sunny weather and daylight, respectively. Then we have $P(C_1|C_2, C_3) = P(C_1|C_2', C_3')$.*

From the data, it appeared that $P(C_1|C_2', C_3') = 0.20$. Using Assumption 3, we have

$$P(C) = P(C_1, C_2, C_3) = P(C_1|C_2', C_3') \cdot P(C_2, C_3) = 0.20. \tag{14}$$

The cut-in scenarios consist of the following activities:

- A_1: The ego vehicle is lane following.
- A_2: The target vehicle is driving in an adjacent lane in the same direction as the ego vehicle.
- A_3: After activity A_2, the target vehicle performs a lane change towards the lane of the ego vehicle, such that the ego vehicle needs to brake.
- A_4: The automation system detects the cut-in.
- A_5: After activity A_4, the automation system activates the brakes of the ego vehicle.

The likelihood of the activities A_1, A_2, and A_3 can be estimated using the data. It is assumed that the ego vehicle needs to brake if the target vehicle is driving slower and the headway time is less than three seconds. In case of a slower target vehicle with a larger headway time, the scenario is referred to as a gap closing scenario [22], [23].

For simplicity, we assume the following:

Assumption 4 *The automation system always detects the cut-in and activates the brakes after detecting the cut-in, such that $P(A_4, A_5|A_1, A_2, A_3, C) = 1$.*

Using this assumption, we can compute $\lambda_{A|C}$ by detecting the number of occurrences of the activities A_1, A_2, and A_3 under the conditions C. Based on the dataset, we have $\lambda_{A|C} = 9.9\,\mathrm{h}^{-1}$, i.e., in each hour that the ego vehicle is driving in a speed range of 60 km/h and 130 km/h, there are on average 9.9 cut-ins with the target vehicle driving slower than the ego vehicle, such that the headway time after the cut-in is less than three seconds. From this, it simply follows that

$$\lambda_{A,C} = \lambda_{A|C} \cdot P(C) = 2.0. \tag{15}$$

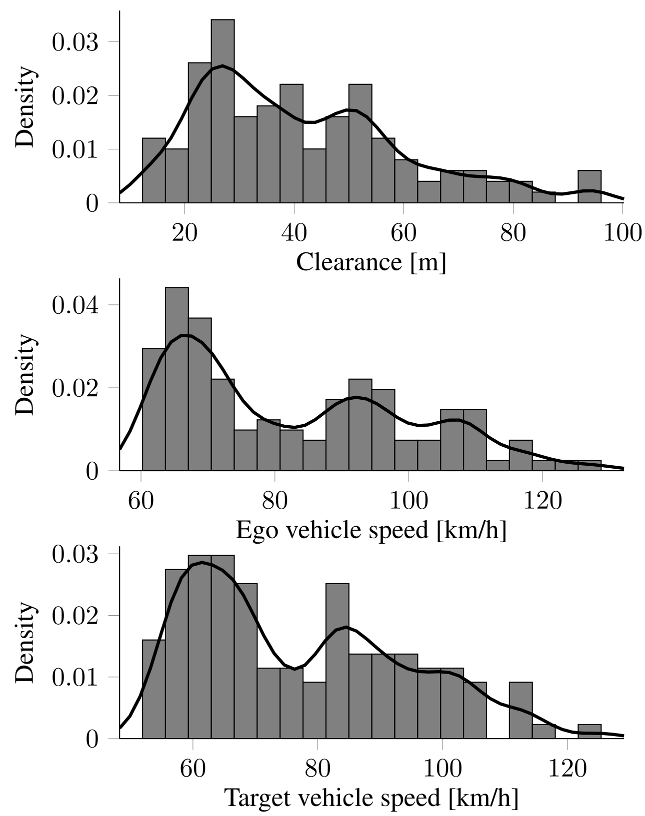

Figure 3: Histogram of the data of the parameters (bars) and their estimated marginal probabilities (lines).

Calculating severity

To limit the number of parameters, we assume the following:

Assumption 5 *The ego vehicle is driving at a constant speed at the moment of the cut-in of the target vehicle, i.e., the moment that the target vehicle enters the lane of the ego vehicle.*

Assumption 6 *The target vehicle is driving at a constant speed.*

Both assumptions can be justified using the data. In case of the ego vehicle, the average acceleration at the moment of the cut-in is $-0.29\,\mathrm{ms}^{-2}$ and the standard deviation equals $0.50\,\mathrm{ms}^{-2}$. In case of the target vehicle, the average deceleration at the moment of the cut-in is $0.05\,\mathrm{ms}^{-2}$ and the standard deviation equals $0.37\,\mathrm{ms}^{-2}$. As a result, the scenario is parametrized using $d = 3$ parameters:

1. The clearance between the target vehicle and the ego vehicle at the moment of the cut-in, i.e., the moment than the target vehicle enters the lane of the ego vehicle.

2. The speed of the ego vehicle at the moment of the cut-in.

3. The speed of the target vehicle throughout the whole scenario.

A histogram of the data of the parameters is shown in Figure 3. The probability density function is estimated using the KDE of Eq. (3) with the Gaussian kernel of Eq. (4). Before applying KDE, the data is scaled, such that the standard deviation equals one for each parameter. We use leave-one-out cross validation to compute the bandwidth h (see also [24]) because this minimizes the Kullback-Leibler divergence between the real underlying pdf and the estimated pdf [13], [25]. The resulting bandwidth equals $h = 0.198$. The marginal probability distributions coming from the resulting joint distribution, i.e. the KDE, are shown in Figure 3 by the black lines.

Let R denote the result of having a collision. Given a certain parameter vector θ, we have $P(R|\theta, A, C) = 1$ if the outcome of the simulation is a collision and $P(R|\theta, A, C) = 0$ otherwise. For the simulation, we used the forward Euler method with a step size of 0.01 s, similar as the sample time of the controller. On a regular computer, approximately 2000 simulations are performed in a second. We performed a million simulations, i.e., $N = 10^6$. In total, 28 simulations ended with a collision, thus, according to Eq. (7), we have:

$$P(R|A, C) = 2.8 \cdot 10^{-5}. \tag{16}$$

Calculating the risk

Let λ denote the average number of collisions with a cut-in scenario as described earlier along the specified route for a vehicle with the automation system as described above. Using Eq. (8), we have:

$$\lambda = \lambda_{A,C} \cdot P(R|A, C) = 5.5 \cdot 10^{-5}\,\mathrm{h}^{-1}. \tag{17}$$

Using Eq. (10), the probability of having no collision in a cut-in scenario as described above during an hour of driving is

$$P(\text{no } R, A, C \text{ during an hour}) = 0.999945. \tag{18}$$

By solving the Poisson distribution of Eq. (9) for λ with $k = 0$, we can also conclude that with 95 % certainty, there will be no collision in a cut-in scenario as described earlier when driving 925 h.

DISCUSSION

We illustrated the applicability of our risk estimation method through an example in the previous section. However, our method has some limitations as well. As an example, many assumptions are made to simplify the calculation of estimated risk or because there are unknowns due to lack of data. These assumptions reduce the accuracy of the estimated risk. Another limitation is that we applied the proposed method for only one type of driving scenario, while the full potential can be better demonstrated by applying the method to a wider range of scenarios.

Despite the mentioned limitations, we believe that our proposed method takes an important step towards objective hazard and risk analysis as we summarize in the following points:

- All the assumptions that were made for estimating the risk are explicit and based on measured data. By making the assumptions explicit, it is much clearer why a certain risk is associated with — in this case — a certain/specific scenario.
- Because our proposed method explicates all the steps and assumptions that lead to a certain estimated risk, it is easily possible to update the risk when more information of the system is known or when more data is available.
- The systematic quantification of the risk provides additional objectified trust in the safety analysis that depends on the availability of data rather than experts judgment.
- The method can be scaled up to be applied to multiple scenarios and operational situations with small modifications.

CONCLUSIONS

As automotive systems move towards higher automation levels, we require formal methods for risk assessment. Currently, however, measuring risk is often based on experts' judgments. Therefore, we propose a method for quantifying the risk assessment as to reduce the risk of subjective errors in the judgment. Our proposed method estimates the risk of a driving scenario while considering the entire operational situations and their relations through analysis of real-world driving data and simulations of the automation system. Our systematic approach for quantifying the risk provides additional trust in the safety analysis, as it depends on the available data rather than experts' judgment.

It remains future work to apply the method for different scenarios to show the full potential of the method. We also aim for extending our method by considering, next to the exposure and the severity, the controllability [26].

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ACCIDENTS INVOLVING CARS IN AUTOMATED MODE – WHICH ACCIDENT SCENARIOS WILL (NOT) BE AVOIDED BY LEVEL 3 SYSTEMS?

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Paper Number 19-0224

ABSTRACT

In the coming years systems will become available that will be able to drive in automated mode for certain periods of time but will only be able to handle selected situations. This is referred to as conditional automation (level 3), whereby the driver no longer has to monitor the vehicle continuously but does have to take control on request when the limits of the automation driving system are reached. What we can say today is that vehicles with different levels of automation will be sharing the roads with manually driven vehicles in the foreseeable future. It is still unclear whether automated vehicles sharing the road with manually driven vehicles will lead to additional road safety risks (mixed traffic). With the presumption that vehicles will still be involved in accidents while they are driving in automated mode, following question arises: how will these accidents look like in the future? The German Insurers Accident Research therefore analyzed the impact of automated driving on motorway accidents. For this study, the UDV used its own accident database (referred to as the UDB) which contains a representative cross-section of all third-party vehicle claim files of the insurers involving personal injury and at least € 15,000 total claim value. The analyzed pool consists of accidents which occurred between 2007 and 2013. In a first step, relevant accident scenarios were determined based on all motorway accidents involving cars in the data pool. In a second step, generic automated driving functions and their characteristics were defined. Thereby, starting with driver assistance and comfort systems (DACS), automation Level 3 and 4 were defined and analyzed. By means of a case-by-case analysis the theoretical benefit potential of these systems was evaluated. Results of the analyses are: It can be expected for the future that cars driving in automated mode will still be involved in accidents. An active Level 3 function as described above could prevent up to 6% more motorway accidents than modern cars equipped with DACS. But negative effects that haven't been quantified up to know may decrease this potential significantly. With these systems it can anticipated that the frequency of rear-end accidents will decrease. But accidents caused by lane change will remain a big challenge for the automated driving systems. With a Level 4 system which drives in automated mode a total of 21% of all motorway accidents were considered as avoidable. The approach used in the study is based on limited knowledge on automated driving available today. It can be stated that the driver is the most critical part up to Level 4 automated driving. Starting with Level 4 this uncertainty will be nearly eliminated. A significant change in the accident situation can be expected only from systems with a very high level of automation (Level 4+) which exclude the driver from the driving task completely. But even with a Level 4 system, accidents will still happen in the future, e.g. due to mixed traffic.

INTRODUCTION

Automated driving is regarded as the future of mobility. It is expected to make traffic flow more efficiently and reduce the number of road accident victims as well as emissions and traffic jams. This will be more of a multi-dimensional, gradual transition than a rapid change. The new technology will be available in both cars and commercial vehicles. Currently, these vehicles offer either Level 2 (partial) or, in the near future, Level 3 (conditional) driving automation, which is typically active only on motorways [1]. As the development of the technology continues, vehicles with higher levels of automation that are also suitable for use in other situations, not just on motorways, will gradually become available. The situation is somewhat different with parking functions. Here, development may proceed more quickly toward highly automated functions. What we can say today is that vehicles with different levels of automation will be sharing the roads with manually driven vehicles in the foreseeable future. This development will affect both cars and commercial vehicles.

GERMAN INSURERS ACCIDENT DATABASE

The accident database of the German Insurers Accident Research (referred to as the UDB) is a database that was set up for accident research purposes. The data collected is conditioned for interdisciplinary purposes for the fields of vehicle safety, transport infrastructure and traffic behavior. The contents of the claim files from the insurers form the basis of the UDB. Only third-party vehicle claims involving personal injury and at least € 15,000 damage costs have been taken into account for the GDV accident database. Cases involving only damage to property and less serious accidents involving personal injury (damage costs < € 15,000) are not included in the UDB

The data sample used in this analysis consists of a total of 3,029 accidents that occurred between the years 2007 and 2013 and involved at least one passenger car. A total of 4,845 cars excluding vans were involved in these accidents. Motorway accidents make up 11% (n=346 relevant cases with n=709 involved cars) of these accidents. All types of traffic involvement were taken into account as the collision parties for the car (cars, trucks, buses, motorcycles, bicycles and pedestrians) as well as single car accidents. Single car accidents are, however, underrepresented, as cases in which there is no injury or damage to a third party are not brought to the attention of GDV.

MOTORWAY ACCIDENTS INVOLVING CARS IN THE UDB

The n=346 motorway accidents in the UDB were broken down in:

- accidents where a car was responsible for the crash (which make up 25% of all involved cars)
- accidents where at least one car was involved but not responsible for the crash (which make up 75% of all involved cars).

Out of these 346 accidents, a total of 146 cases where the car was responsible for the crash and 244 cases where the car was not responsible for the crash have been analyzed. The fact that more than one car may be involved in an accident led to multiple counting, i.e. the same case can be counted more than once.

Motorway accidents where the car was the main responsible

Motorway accidents can be described in different ways. The most common method is by using the parameters "Type of accident" [2] and "Kind of accident" [3]. In this study, a combination of both parameters was used first for a rough classification of the UDB accidents in scenarios and, in addition, a case-by-case analysis was performed in order to break them down in sub-scenarios. The type of first conflict between the case-car and another vehicle was the decisive factor in this matter.

Two major scenarios were found to be predominating and these acount for a total of 88% of all n=164 motorway accidents caused by a car. These are:

- "rear-end accidents" (51%) and
- "lane change accidents" (37%).

There is also a small group of "other" accidents (13%) which can not be put in patterns. These are conflicts with crossing animals, for instance, or rear-end collisions where the case-car was hit from behind after a lane change. Since the vehicle coming from behind was very fast and/or far away at time of lane change, these accidents were not assorted to the group of lane change accidents.

Rear-end accidents are characterized by the fact that the case-car is involved in one or multiple collisions after a conflict with a moving or stationary vehicle in front of it in the same lane. In most of the cases the driver of the case-car oversaw the vehicle ahead or failed reacting properly when approaching it.

Lane change accidents are characterized by the fact that the case-car is involved in one or multiple collisions after having left either intentionally (lane change in order to avoid a rear-end collision with the vehicle ahead) or unintentionally (e.g. due to driver distraction, fatique) its own driving lane.

A closer look at the sub-scenarios shows that:

- Unintentional lane changes of the case-car represent the most frequent sub-scenario and account for one third of all all motorway accidents caused by a car.
- Rear-end conflicts with a stationary vehicle, as typical for congestion related situations, are the second most frequent sub-scenario and make up 31% of all mtorway accidents caused by a car.

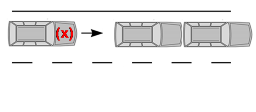
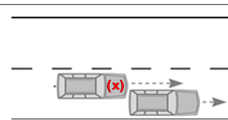
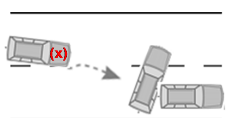
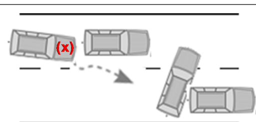
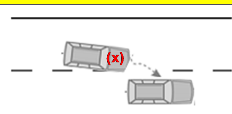
Motorway accidents that were caused by a car (n=164)			
Accident scenarios from the view of the case-car that caused the accident (x)		n	%
Total accidents		164	100
Rear-end		83	51
	Conflict between the case-car and a stationary vehicle in front in the same lane	51	31
	Conflict between the case-car and a vehicle moving ahead in the same lane	32	20
Lane change		60	37
	Conflict between case-car and another vehicle in the same or another lane caused by an unintentional lane change of the case-car	54	33
	Conflict between case-car and another vehicle caused by an intentional lane change of the case-car due to a vehicle on the same lane	6	4
Others		21	13
	Other conflicts (e.g. lane change of the case-car due to another lane changing vehicle or case-car being hit by a vehicle from the adjacent lane)	21	13

Figure 1. Motorways accidents caused by a car and their classification in scenarios and sub-scenarios

Motorway accidents where the car was involved but not responsible

The groupf of accidents where the car was involved but not responsible for the crash build the second pool. It contains 244 accidents and makes up a larger proportion within all motorway accidents invoving a car in the UDB (n=346).

A short overview of the main and sub-scenarios (Figure 2) reveals a picture which is similar to that observed for accidents with the car being responsible. Rear-end-collisions have the highest share, accounting for 51% of the cases being followed by the group of lane change accidents with a share of 41%.

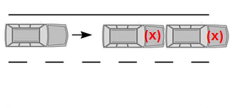
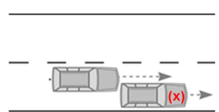
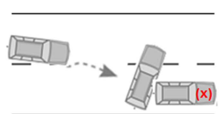
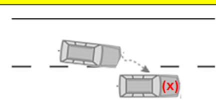
Motorway accidents that were not caused by a car (n=244)			
Accident scenarios from the view of the case-cars that were invovled but not responsible for the accident (x)		n	%
Total accidents		164	100
Rear-end			
	Another vehicle collides with the case-car which is standing in the traffic in the same lane	79	32
	Another vehicle collides with the case-car which is moving ahead in the same lane	46	19
Lane change			
	Another vehicle collides with the case-car after a lane-change (different collision constellations possible)	99	41
Others			
	Other conflicts (e.g. case-car is hit by a vehicle that is moving on the adjacent lane)	20	8

Figure 2. Motorways accidents caused by a car and their classification in scenarios and sub-scenarios

CATEGORIZING AND DISTINGUISHING BETWEEN MODERN ASSISTANCE AND AUTOMATED FUNCTIONS

The discussion around automated driving requires a clear understanding of the attributes and capabilities of the functions involved. Driving can be subdivided into navigation, vehicle control and stabilization tasks [4]. According to this model, the navigation level is about route planning, the vehicle control level involves the driver comparing the goal with the current situation (i.e. dynamic driving), and the stabilization level is about controlling deviations in a closed loop system.

Assistance and automation functions operate on the vehicle control level. There are three different modes of action here [5]: informative and warning functions, continuously automating functions and temporarily intervening systems (see table 1). This approach has the advantage that a distinction can be drawn between advanced driver assistance systems and automated driving functions. Even among advanced driver assistance systems, there are differences that are clearly based on their mode of action. Mode of action B describes the levels of automation under discussion (see table 2). Level 1 covers only advanced driver assistance systems that handle longitudinal and lateral control. These are the proximity control system and the lane-keeping assist system. The lane-departure warning system, on the other hand, comes under mode of action A/2.

Mode of action A Informative and warning functions	Mode of action B Functions offering continuous automation	Mode of action C Systems that intervene temporarily in accident-prone situations
Take effect exclusively and "indirectly" through the driver: 1. Status information, e.g. traffic-sign recognition 2. Abstract warning, e.g. lane-departure warning system 3. Concrete warning, e.g. • Blind-spot detection system or • Collision warning system	Have a direct effect on vehicle control, can always be overriden. Definition according to SAE J3016 [1] or VDA/BASt [4]	Preventive machine intervention with a negative situation forecast, e.g. • Emergency brake assist system • Emergency steering assist system

Table 1. Assistance and automation functions on the vehicle control level [4]

Nomenclature	Driving tasks of the driver by level of automation
Full automation Level 5	The system takes full control of driving on all road types and in all speed ranges and environmental conditions
High automation Level 4	The system takes over full lateral and longitudinal control in a defined application
Conditional automation Level 3	The system takes over lateral and longitudinal control for a certain period in specific situations
Partial automation Level 2	The system takes over lateral and longitudinal control (for a certain period and/or in specific situations)
Driver assistance Level 1	The driver has constant lateral or longitudinal control. The other driving task is handled by the system within certain limits (e.g. adaptive cruise control (ACC) system, lane-keeping assist system).
No automation Level 0	The driver drives constantly (for the whole journey) with both longitudinal control (acceleration and breaking) and lateral control (steering).

Table 2. Levels of automation in accordance with SAE J3016 and VDA/BASt [1,6]

METHOD DESCRIPTION

An overview of the analysis method and some specifications related to the automated driving systems will be given in the following.

For each motorway accident in the UDB, the car that caused the accident was defined as the case-car. In a case-by-case analysis, the safety potential was estimated for driver assistance and comfort systems (DACS) and two levels of automated driving. The cases were analyzed using the "What would happen if..." method. The prerequisite for this is the assumption that none of the analyzed case-cars involved was using an automated function or any DACS at that time. This approach considers the course of the accident as it happened in reality and contrasts it with the course of the accident as it would have been with the case-car driving in automated mode or with DACS. This makes it possible to determine the influence an automated ride would have had on the course of the accident. The original driver behaviour was taken into consideration, as far as it was possible. For each case it was assumed that during the automated ride the driver of the case-car would have behaved in the same way as he did before the original accident.

The challenging part was to define the automated driving functions and implement them in the analyses. An attempt was made to use the knowledge on the system definitions gained from the previous chapter. However, this could not be done in that detail as described in Table 1 and Table 2. When speaking of retrospective accident analysis, a clear distinction between DACS and automation systems is almost impossible. It could not always be determined which system would have intervended first in case of an accident: DACS or the automated system. The "What would happen if..." method uses the assumption that the case-car was driving in automated mode right before the accident, but does not consider earlier traffic events that could have been influenced by the automated ride.

With this limitations and being aware of the fact that we were not exactly in line with the definitions in Table 2, three degrees of systems were defined and their boundary conditions were set. It was assumed that every case-car (and no other vehicle involved) was equipped with following driver assistance and comfort systems (DACS):

- Adaptive cruise control (ACC),
- Emergency braking assist,
- Lane keeping assist and
- Blind spot detection system.

In simply terms spoken, these four DACS are pieces of a Level 1 and in combination a Level 2 automated driving mode. Additonal two more levels were then defined by succesively adding more attributes and capabilities. These levels were Level 3 and Level 4. Table 3 gives a short description of the systems with their boundary conditions.

It has to be underlined that with this method no differentiation could be made between DACS, Level 1 and Level 2. These differences lie mostly in the Human-Machine-Interface – with the full responsibility of the driver - and not in technical details of the systems. These human based differences can also not be adressed with the tool of a retrospective accident analysis. In the following parts of this paper, the term DACS will therefore be used for this group of systems.

It was possible to distinguish between these DACS, Level 3 and Level 4. The differences in the functionalities can be basically described by the situations that can be handled by the systems. But the most crucial difference between DACS and Level 3 was that, for DACS, the driver behaviour"overwrote" the system functionality in certain situations. This was not done for a Level 3 system because, according to the definitions, the driver was not monitoring during the automated ride. Following aspects were essential when declaring no safety potential to the systems:

- System reaches its technical boundaries (see Table 3)
- System is not activated or manually switched off by the driver
- Unforseen environmental or car related events (aquaplaning, tire blow, technical failure of the car).

The analyses did also not consider following aspects that could lead to negative effects for road safety but which are not quantified yet:

- Take-over request to the driver [7]
- Negative effects initiated by the automated ride that could lead to other accidents (e.g. fatique) [8]
- Different driver behaviour due to mixed traffic.

<table>
<tr>
<td>
Assumptions for DACS:

o System maintains longitudinal and lateral drive, but no lane change
o Driver can override or switch off the system
o Driver acts / monitors the system continuously (hands on the steering wheel)
o System performs braking manoeuvers but no evasive steering manouvers (only warning)
o System has no safety potential in following cases:
▪ Construction sites
▪ Joining or leaving the motorway
▪ Steering mistake by the driver
▪ Alcohol, fatigue and physical issues of the driver
▪ Technical failure of the car
▪ Extreme weather conditions (strong rain, aquaplaning).
</td>
<td>
Assumptions for a Level 3 automated driving function:

o System operates up to 130 kph (not considered in this analysis)
o System maintains longitudinal and lateral drive (except: entering and leaving the motorway)
o Driver can override or switch off the system
o System performs braking, lane change (evasive) and overtaking manouvers
o Driver is not required to monitor the system
o Driver receives a take-over-request in critical situations
o System has no safety potential in following cases:
▪ Construction sites
▪ Joining or leaving the motorway
▪ Alcohol and severe physical issues of the driver
▪ Technical failure of the car
▪ Extreme weather conditions (strong rain, aquaplaning).
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<td colspan="2">
Assumptions for a Level 4 automated driving function:

o System operates up to 130 kph (not considered in this analysis)
o System maintains longitudinal and lateral drive (incl. entering or leaving the motorway)
o Driver can override or switch off the system
o System performs braking, lane change and overtaking manouvers
o Driver is not required to monitor the system
o System performs braking and evasive manouvers
o In critical situations, the system initiates a minimal risk manouver
o Systems has no safety potential in following cases:
▪ Technical failure of the car
▪ Extreme weather conditions (strong rain, aquaplaning).
▪ Collisions with other vehicles that approach from the site or from behind
</td>
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</table>

Table 3. Boundary conditions for the three defined levels of automation in the UDB analysis

SAFETY POTENTIAL FOR SELECTED LEVELS OF AUTOMATION

The safety benefits were calculated for each of the systems separately and were then put in relation to the different accident pools (see Table 4).

A modern car equipped with DACS could achieve a safety potential of 21% on motorways. This underlines the important part of driver assistance systems for road safety. As already mentioned before, with this method, this equals the safety benefit of a Level 1 and Level 2 system. That means that no additional safety benefits can be expected for Level 1 and Level 2 but negative effects might lead to less benefit at this point (see Figure 3).

Related to all motorway accidents involving a car, an additional safety potential of +6% could be achieved by a Level 3 system. This “ad on” is small and can be explained by the fact that a Level 3 system still has to rely on the driver as a back-up when the technical boundaries of the system are reached (see also Table 3). And it has to be put in contrast to possible negative effcts caused by a Level 3 system.

A nearly maximum safety potential of additional +21% can be achieved by a high automation level (Level 4), which requires no driver monitoring or driver intervention at all during the autonomous ride. Even here, possible negative effects (mixed traffic) must be considered. According to the analyses, with a Level 4 system, more than half of all motorway accidents caused by a car would still remain unavoidable, for instance.

If these benefits are put in relation to the larger accident pools, their amount will decrease. Related to all accidents involving a car in the UDB, for instance, the achievable safety potential for a Level 3 system system is 0.7% and even with a Level 4 maximum 2.4% more car accidents could be avoided.

Systems		**Safety benefit [%] in terms of avoidable accidents as an "ad-on" to the achievable benefits by ADAS**			
		Motorway accidents involving a car (n=346)	Motorway accidents caused by a car (n=164)	All accidents involving a car (n=3,029)	All accidents caused by a car (1,834)
DACS		**21%**	**45%**	**2.5%**	**4.0%**
Level 3	additional	**6%**	**12%**	**0.7%**	**1.1%**
Level 4	additional	**21%**	**45%**	**2.4%**	**4%**

Table 4. Achievable safety benefits for analyzed levels of automated driving functions in relation to the different accident pools – the numbers for Level 3 and 4 represent the additional benefits in comparison with DACS

For those accidents that were caused by a car on motorways, Table 5 gives a differentiated view of the achievable safety benefits for the two main accident scenarios. DACS could avoid 80% of all rear-end accidents in the case material but only 10% of the lane change accidents. This is not surprizing because it reflects what DACS in modern cars can already achieve. Todays DACS already overcome most rear-end conflict situations. But most lane change situations are still critical for them [9].

In comparison to DACS, the additional benefit of a Level 3 system can be derived from better skills in the form of dealing with lane change situations. In the analyzed case material, a Level 3 system could avoid only few more rear-end accidents (factor 1.1) but nearly three times more lane change accidents than DACS (see Table 4). For a Level 4 system there is almost no difference between the share of the two scenarios. Due to the exclusion of the driver from monitoring/intervening during the automated ride, a Level 4 system will be able to overcome all types of conflicts in longitudinal traffic properly, i.e. a lane change will be also no problem anymore for self-caused accidents.

Motorway accidents that were caused by a car (n=164)					
Accident scenarios	n	%	avoidable accidents [%]		
			DACS	**Level 3**	**Level 4**
	164	100	**35**	**49**	**91**
Rear-end	83	51	**80**	**87**	**98**
Lane change	60	37	**10**	**27**	**97**

Table 5. Achievable safety benefits for selected automation levels in the UDB

DISCUSSION - ACCIDENTS AND AUTOMATED DRIVING?

One major outcome of the analyses is that there still will be accidents caused by the car during a Level 3 automated ride in the future, regardless the achievable safety benefits of the system. The main reason is that an automated ride with a Level 3 system will still need the driver in terms of intervening in the event of critical situations.

The fundamental problem in connection with constant monitoring coupled with intervention in the event of critical situations is based on a human characteristic investigated by psychologists over 100 years ago [10]. The resulting Yerkes-Dodson law describes the general relationship between a person's ability to perform well and their state of physiological and mental arousal. When a person has a low level of arousal, their performance remains at a minimum level. As the person becomes more aroused, their performance increases up to a maximum level. If arousal increases beyond that, performance starts to drop again until it reaches a similar minimum level to the level at low arousal (Figure 3). Put simply, this means that people perform demanding tasks best with a moderate level of arousal. Driving a car is such a task. Monotonous tasks, like driving down a perfectly straight road with no traffic, can result in a low level of performance or failure. Monitoring a Level 2 system is one such task. Equally, if a driver is overtaxed, the result will be poor performance and even failure. Suddenly being requested to take over control from a Level 3 system would be an example of this.

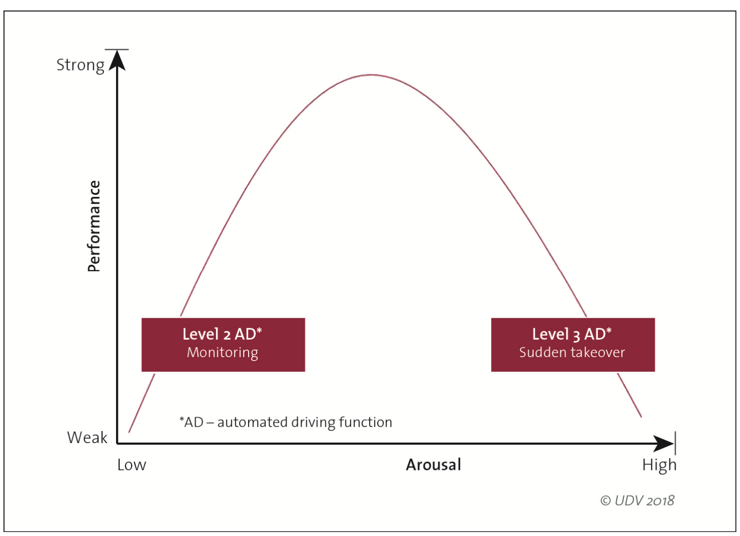

Figure 3. Simplified representation of the Yerkes-Dodson law in connection with automated driving [10]

CONCLUSIONS

The analyses revealed that 11% of all accidents involving a car occur on motorways. For accidents that were caused by a car, safety benefits were determined based on two levels of automated driving. The most substantial benefit in terms of 21% avoidable accidents can be expected from modern assistance and comfort systems (DACS) if these consist of an emergency breaking assist, a lane change assist, a blind spot detection system and an adaptive cruise control.

In comparison to modern cars equipped with DACS, an additional benefit of +6% could be expected for a Level 3 system in terms of avoidable accidents on motorways. Compared to the benefits of DACS, this level of automation might have a higher benefit because it will be able to avoid more lane change accidents. Nevertheless it has to be considered that there could be negative effects on road safety caused by a Level 3 system. Up to know, these effects have not been quantified yet. But studies indicate that they should not be underestimated and that these negative effects might reduce the additional positive benefits. In total, Level 3 systems might have no additional positive effects at all.

It can be predicted that cars driving in a Level 3 automated mode will still cause accidents on motorways in the near future. And they will also be even more often involved in accidents without their own fault. The most critical part for a Level 3 in the future will still be the driver. The majority of those accidents that can not be avoided by a Level 3 system will be lane change accidents.

Only a Level 4 system will provide a high benefit in terms of additional 21% avoidable accidents compared to a Level 3 system. This is because a Level 4 system will be able to handle almost all traffic situations properly but most importantly, the critical part "driver" will be nearly eliminated during the automated ride. Nonetheless, even with a Level 4 system, a large proportion motorway accidents involvoing a car will still remain unavoidable. In this context, possible negative effects of mixed traffic are not considered here.

From the view of the German Insurers, highly automated vehicles (Level 4) could bring great benefits in terms of road safety if they functioned flawlessly under all conditions within their intended scope. Until such time as these systems come onto the market, drivers of manually controlled vehicles should benefit in terms of road safety from continual improvements in driver assistance systems.

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AN OPTIMIZATION-BASED METHOD TO IDENTIFY RELEVANT SCENARIOS FOR TYPE APPROVAL OF AUTOMATED VEHICLES

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Paper Number 19-0024

ABSTRACT

The objective of this paper is to propose a novel approach for an intelligent selection of relevant scenarios for the certification of automated vehicles. During this process, two main challenges occur. Firstly, since the number of possible traffic situations is unlimited, a selection of a manageable number of representative situations to be tested must be applied during the certification of automated vehicles. Secondly, nowadays a limited number of standardized test cases are used for the type approval of vehicles. This can lead to so-called gaming of tests, which means that the manufacturer optimizes the system's performance in the predefined test cases. A prominent example are the current discussions about the large differences between the emissions of vehicles in the driving cycle (e.g., WLTP) and in everyday use in road traffic. This paper addresses both stated challenges and exemplifies a method for the system-specific selection of test cases for the certification of automated vehicles, which are not known to the manufacturer in advance. Based on a system analysis and an objective driving behavior characterization, weak spots of the system under test are identified and connected to complex scenarios to be tested. This approach allows an economic and meaningful certification process for automated vehicles.

INTRODUCTION

In recent years, intensive work has been carried out on the implementation of highly automated and autonomous vehicles (Level 3 and higher according to the SAE classification [1]). Many manufacturers already have prototypes of these vehicles, which are increasingly being tested in real traffic, especially in the USA. A high level of safety is indispensable for social acceptance - especially due to the danger posed to uninvolved parties in the event of system faults.

It is difficult to prove the safety of automated vehicles in an economically feasible manner, due to the open parameter space. For the type approval of vehicles, in particular, only a very limited scope can be tested. Therefore, an intelligent and manufacturer-unknown selection of the scenarios to be tested is necessary in order to avoid the so-called gaming of tests and to prove a sufficient safety performance. In addition, regulations and laws for the certification of automated vehicles are still missing.

In general, due to the infinite number of possible traffic situations, there is a need for an economically feasible method of performing safety assessments on automated vehicles. A promising approach is scenario-based testing. Based on the assumption that a large part of traffic situations is irrelevant and uncritical, scenario-based testing is limited to meaningful events (scenarios). The framework for this approach is being developed, for example, in the German funding project PEGASUS [2]. The challenge of selecting and finding all relevant scenarios remains with this approach. Since only an extremely limited number of tests can be carried out during certification, it is particularly important for this application to conduct an intelligent selection of scenarios. This contribution, therefore, presents a novel approach for a system-specific selection of relevant scenarios for the certification of automated vehicles. Furthermore, with this approach, the manufacturer can no longer perform so-called gaming of tests.

The article is structured as follows: First, an overview of existing literature is given, and the research objective is derived. Subsequently, the procedure developed is described in detail in the METHODOLOGY section. An exemplary derivation of results using the method presented is explained in the RESULTS section. Then, the approach will be critically discussed, and its limitations demonstrated. The paper concludes with a summary and an outlook on future work.

LITERATURE REVIEW AND RESEARCH OBJECTIVE

This section addresses in detail the challenges already raised in the introduction regarding the certification of automated vehicles. Finally, the state of the art is critically evaluated, and the main research question of this paper is derived.

Unlimited number of possible traffic situations

Due to the infinite number of possible traffic situations, the safety assessment of automated vehicles can no longer be carried out economically in road tests [3]. With the scenario-based approach, the level of effort required can be reduced considerably if possible traffic situations are restricted to relevant events. Irrelevant situations, such as driving in a straight line with no action taken by drivers in surrounding traffic are left out. Nevertheless, the challenging task of finding all relevant scenarios remains with this approach. Before we examine existing methods for the selection of these scenarios in detail, important terms are defined.

Definition of vocabulary

Object and Event Detection and Response (OEDR): Different factors influence the safety of automated vehicles. These are, for example, the human machine interface (HMI) as well as the functional safety and cyber security of the vehicle. In our approach, we focus on Object and Event Detection and Response (OEDR) according to NHTSA [4, p. 7]. OEDR includes the detection of objects, their classification, the planning of a suitable response to the detected object and the execution of the planned action.

Operational Design Domain (ODD): According to SAE [1], the ODD is defined by the area for which the automated vehicle was developed. The ODD can be restricted, for example, by road classes (e.g., highway or city center) or environmental conditions (e.g., weather conditions).

System Under Test (SUT): The automated vehicle to be tested and certified is denoted as system under test.

Traffic Participant (TP): All kinds of movable objects within a traffic situation are called traffic participants. Among others, this includes pedestrians, cyclists, motorcycles, passenger cars and trucks.

Scenario: ULBRICH [5] defines a scenario as:

> *[…] the temporal development between several scenes in a sequence of scenes. Every scenario starts with an initial scene. Actions & events as well as goals & values may be specified to characterize this temporal development in a scenario. Other than a scene, a scenario spans a certain amount of time.*

Where a scene is defined as:

> *[…] a snapshot of the environment including the scenery and dynamic elements, as well as all actors' and observers' self-representations, and the relationships among those entities. Only a scene representation in a simulated world can be all-encompassing (objective scene, ground truth). In the real world it is incomplete, incorrect, uncertain, and from one or several observers' points of view (subjective scene).*

Furthermore, MENZEL [6] distinguishes between three types of scenario – functional, logical and concrete scenarios. Functional scenarios represent a linguistic description of the scenario on a semantic level. The information content of this description is low. For logical scenarios, the parameters required to describe the scenario, such as the initial speed of the SUT or the lane widths, as well as their ranges are included. Concrete scenarios have the most information content. Starting from a logical scenario, a specific value is defined for each parameter in the concrete scenarios and is thus unambiguous. It should also be noted that the term test case is used here as a synonym for a concrete scenario, although in [7] the test case also includes pass-fail criteria. In the present use case, pass-fail criteria can be regarded as prescribed by future regulations for the type approval of automated vehicles.

Relevant scenarios: All scenarios that contribute to the type approval of automated vehicles are considered relevant. Relevant scenarios can also be very simple, such as the beginning of a speed limit. This is relevant for certification because an automated vehicle must comply with existing traffic regulations. This type of scenario is taken into account in the method developed when driving behavior is characterized. A subset of the relevant scenarios are critical and complex scenarios (Figure 1). These two subsets are defined below.

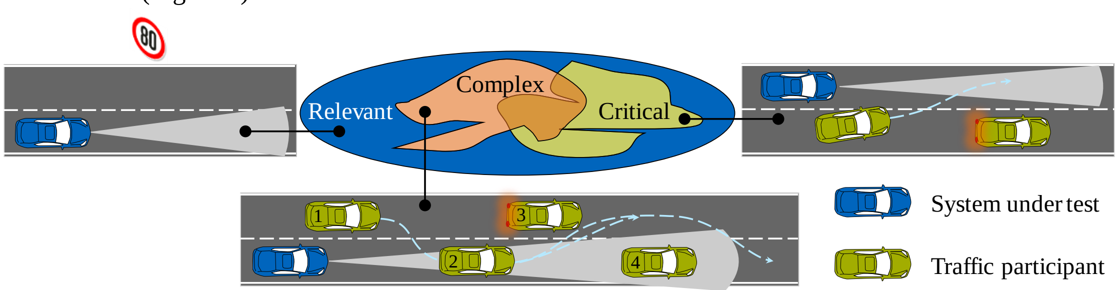

Figure 1. Definition of relevant, complex and critical scenarios

Complex scenarios: Complex scenarios are scenarios that present a challenge for the planning algorithm of the SUT. This is achieved by the presence and movement of other TPs. Complexity can thus be understood as how difficult it is for the planning algorithm to plan a safe trajectory under consideration of other TPs. Other influences such as the width of the road or the need to maneuver are not explicitly taken into account in this method.

Critical scenarios: Criticality is defined in this paper as the closeness to an accident. To measure criticality, indicators such as Time-To-Collision (TTC) [8] can be used. The smaller the value of this indicator, the more critical the scenario is. Critical scenarios can have two different causes. On the one hand, they can arise due to high differential speeds and small distances. This means that a logical scenario is not inherently critical. However, a critical concrete scenario can very easily be derived from any logical scenario if the distances between the objects and their velocities are adjusted accordingly. Thus, a cut-in situation is not automatically critical. But if a slow-moving TP changes into the SUT's lane at a short distance before it, it is very critical. These types of critical scenarios can be defined without extensive analysis and will not, therefore, be considered further in this publication. On the other hand, critical situations can arise due to errors of the SUT. These can be errors and inaccuracies in perception and errors in the planning algorithm. The former is considered in the developed methodology in the analysis of the sensor setup, while the latter is addressed in the complexity of the traffic situations. It is assumed that increasing complexity increases the probability of an error in the planning algorithm. An example of a critical scenario due to an error in the SUT is a (complex) traffic situation in which the SUT incorrectly predicts the trajectory of a TP, resulting in an accident in the further progress of the scenario. Since this type of criticality is taken into account in the methodology by the analysis of the sensor setup used and also by the addition of complexity, the identification of critical scenarios is no longer explicitly discussed in the following.

In summary, it can be concluded that relevant scenarios may be very simple (e.g., speed limitation). In addition, critical scenarios are not automatically complex (e.g., accident involving an autonomous prototype in the USA [9]) and, on the other hand, not all complex scenarios are automatically critical (e.g., if the algorithm masters the scenario correctly). Nevertheless, all types of scenarios mentioned are relevant for the type approval of automated vehicles.

Five-layer model: To define the required parameters for the scenarios in a systematic manner, SCHULDT [10] introduces a four-layer model, which BAGSCHIK [11] extends to a five-layer model. This allows all relevant parameters for the following five layers to be defined:

- Road-level (L1)
- Traffic infrastructure (L2)
- Temporary manipulation of L1 and L2 (L3)
- Objects (L4)
- Environment (L5)

The five layers also contain continuous parameters. These include, for example, the speed of other objects. More specifically, this may be the speed of a traffic participant cutting in front of the SUT. Through the theoretically infinitely fine discretization of continuous parameters, an infinite number of concrete scenarios can be defined. In addition, each concrete value of a parameter can be combined with any other value of the remaining parameters, which corresponds to the so-called N-wise testing. Consequently, the scenario-based approach also requires a methodology that identifies relevant test cases. For this reason, an outline of existing procedures in the literature for selecting and reducing concrete scenarios is given below.

Scenario selection and reduction methods

Instead of combining all values of one parameter with every other parameter (N-wise testing), an intelligent selection of parameter combinations is chosen during the Design of Experiments (DoE). According to KUHN [12], DoE-approaches can be used for complex software systems, because only the combination of a few parameters is sufficient to cause a faulty behavior of the system, which is expressed by the failure triggering fault interaction (FTFI) number. At NASA, for example, the combination of only six parameters covers almost 100 % of the errors occurring [12]. Further information on various methods of DoE, such as covering arrays, as well as the application in the field of automated driving, can be found in [13–16].

+ Good parameter space coverage
– The selection of important parameters is difficult in advance
– No selection of test cases based on relevance

SAATY [17] provides the basis for an approach to detect important parameters and their connection using the Analytic Hierarchy Process (AHP). XIA [18, 19] takes this as a basis and uses the AHP, in combination with an expert knowledge-based analysis of key influencing factors. The scenarios generated are evaluated using a complexity index.

+ Analytical method for the determination of relevant parameters
+ Creation of complex scenarios
– Requires expert knowledge
– Does not consider presumably simple scenarios that nevertheless lead to faulty behavior

An approach that relies entirely on expert knowledge is the creation of scenarios with the help of ontologies [11, 20, 21]. Ontologies are a formal representation of knowledge and its relations, which have their origin in the Semantic Web. Starting from the definition of knowledge, for which the five-layer model by BAGSCHIK [11] described above can be used as a basis, scenes are automatically derived to safeguard the automated driving function. Scenarios can be created by sequencing individual scenes. Furthermore, knowledge-based approaches ensure that elements from the knowledge base can also be found in the scenes and scenarios created. For example, if a pedestrian is defined in the knowledge base, it can be ensured that there are also test scenarios that contain a pedestrian.

- \+ Elements defined in the knowledge base are also part of the test catalog
- – Solely based on expert knowledge
- – No evidence of the relevance of the defined scenarios for the proof of safety

Instead of using expert knowledge, test scenarios for automated driving can also be based on real and simulated traffic situations with a high level of criticality. All extracted scenarios can be stored in a database. This approach, with a database filled with scenarios as the central element of the validation procedure, is used in the German-funded project PEGASUS [22, 23]. In addition to the data sources already mentioned, in principle all possible sources of scenarios can be taken into account. For example, these can also be scenarios from a knowledge-based approach.

- \+ Inclusion of scenarios of various origins possible
- – High storage requirements with nearly identical scenarios
- – If the number of stored scenarios exceeds a manageable number, a method for selecting relevant scenarios is required again

Existing accident databases can also be used to select relevant scenarios [24]. Accident scenarios are reconstructed in simulation and examinations are performed to establish whether the accident could have been prevented or mitigated by the automated driving function to be tested. The prerequisite for this is detailed accident data that contains information about the pre-crash trajectories of the vehicles involved in the accident scenario. These currently only exist for driver assistance systems. Consequently, the significance of the safety level of automated vehicles based on these accidents is extremely limited. This can be improved by further varying the parameters, such as the ego speed.

- \+ Shows accident avoidance potential of the automated vehicle
- – Detailed accident data required
- – Provides only limited information on new risks and accidents introduced by the automated vehicle

Another method based on real driving data from human drivers is the accelerated evaluation of automated vehicles [25–28]. Based on the real driving data of a maneuver (e.g., cut-in), frequency distributions of the parameters involved (e.g., relative speed) are determined. These parameter distributions are adapted in such a way that more severe situations arise that can be used for the accelerated evaluation of the SUT. The importance sampling theory is used to ensure that the accelerated result is valid, and that the acceleration factor can be calculated. Thus, a factor of up to 10^5 can be achieved, which means that each simulated kilometer corresponds to a real distance of 10^5 kilometers.

- \+ Conversion from simulated to real life traffic kilometers
- \+ Straightforward comparability with human performance through, for example, kilometers per accident
- – Frequency distributions of all relevant parameters necessary → time-consuming and cost-intensive data collection
- – Number of necessary involved parameters unknown

The aim of [29–32] is to adapt existing logical scenarios in such a way that relevant, and as critical as possible, concrete scenarios can be created based on them. Starting from a baseline scenario, the trajectories of road users are adapted in such a way that the planning of a safe trajectory for the automated vehicle becomes particularly challenging. Starting with the start scene, the possible trajectories of the road users are predicted into the future. The Reachable Sets, for example, can be used here. All areas in which no other road users can be located in the future are considered safe. Minimizing these safe areas results in particularly important situations for the trajectory planning module of the SUT.

- \+ Also suitable for online evaluation of the selected ego trajectory
- – Trajectory planning is more the focus of the tests than the overall system

While all previously explained procedures evaluate scenarios before they are executed, and optimize them with regard to criticality, critical scenarios can also be derived with the help of simulation executions [14, 33]. A concrete scenario is chosen as the starting point, executed in simulation and evaluated using a criticality metric. Subsequently, specific parameters of the scenario are varied and the change in criticality is evaluated. To maximize criticality during optimization, classical optimization methods [14] as well as machine learning approaches [33] can be used. Theoretically, this approach is also possible in real experiments, but due to the high number of experiments, this is not feasible.

+ Criticality optimization during test execution ensures that critical scenarios are discovered
– Numerous simulations of concrete scenarios required → Particularly time and cost-intensive when high-fidelity simulation models for vehicle dynamics, sensors and environment are used

One approach to reducing the number of relevant scenarios that can be used in parallel to the methods mentioned above is functional decomposition. Based on the decomposition of the human driving task into five layers by GRAAB [34], AMERSBACH [35, 36] adapted this division to fit automated vehicles, using a six layer model. This division can be seen as a further subdivision of the well-known sense-plan-act principle. The aim is to reduce the number of relevant scenarios by considering the individual functional levels separately. For example, to test layer three (situation understanding), all parameters that have no influence on this layer can be omitted.

+ Approach can be used in parallel with other scenario selection methods
– Tests at overall system level are still necessary
– Reduction of the number of scenarios in the overall assessment not yet conclusively clarified

As a final method for the reduction and selection of relevant scenarios for the safety verification of automated vehicles, the formal methods will be introduced [37–39]. The aim of this approach is a mathematical proof of the safety of the SUT. If this proof is successful, then the formal methods are the most effective reduction method, because all tests, whether in simulation or in real tests, become obsolete. This currently fails because of assumptions that must be made but that do not correspond to reality. For example, the authors of [39] assume that the automated vehicle can always precisely determine the current coefficient of friction. However, the exact online determination of the coefficient of friction has been an unsolved problem for years.

+ If formal proof is provided, no tests need to be carried out
– Assumptions must be made that do not accurately reflect reality
– Whether or not driving behavior according to the formal methods leads to unreasonably defensive behavior has not yet been conclusively determined
– It must be demonstrated that an automated vehicle is implemented according to formal methods

Gaming of tests during type approval

As already mentioned in the INTRODUCTION, type approval of automated vehicles is the central application of this publication. In this context, gaming of tests is referred to as a performance optimization towards the standardized test cases. For type approval, the regulations of the UNECE[1] are relevant for the European area. These regulations must be tested by a technical service and confirmed to be complied with so that a new vehicle model can be introduced onto the market in the countries of the contracting parties. To this day, the UNECE regulations for the type approval of vehicles have made significant effort to ensure comparability and reproducibility. For this reason, the test execution, environmental conditions and evaluation of the tests are defined precisely in the regulations. This offers vehicle manufacturers the advantage of knowing in advance which tests are to be carried out, and of optimizing the performance of their systems within these test cases. A reliable statement about the system's behavior in real traffic conditions is, therefore, only possible to a limited extent, as the problems in the emission tests starting in September 2015 [40] clearly revealed.

With regard to vehicle emissions, UNECE Regulation 83 Revision 5 [41] is relevant for vehicle approval. In addition, the UNECE Global Technical Regulation 15 [42], which applies to a larger number of contracting parties (e.g., including the USA), specifies the Worldwide Harmonized Light Vehicle Test Procedure (WLTP). These two regulations stipulate the exact procedure for carrying out the tests and the ambient conditions to be satisfied. On October 10th, 2017, the UNECE clarified in Amendment 5 to Regulation 83 Revision 5 that the Contracting Parties using this Regulation in combination with Global Technical Regulation 15 (WLTP) no longer have to accept type approval on the basis of these Regulations as an alternative to their national/regional laws. The UNECE is currently revising the regulations within the Working Party on Pollution and Energy (GRPE), so that they reflect the actual emissions in real traffic more accurately [43][44, p. 2] and the results thus correspond better to actual driving behavior. By 2020, new regulations shall be adopted on the basis of test procedures already developed by other organizations (e.g., the European Union) [43]. The European Union already introduced its own methods and approval regulations in September 2017, which determine Real Driving Emissions (RDE) in a test procedure under real driving conditions [45]. The 100-percent reproducibility is thereby limited at the expense of better transferability to real traffic events.

[1] https://www.unece.org/info/ece-homepage.html

Initial tendencies exist not only in the area of emissions, but also in assisted driving, to reduce the exact reproducibility for a higher significance under real traffic conditions. In assisted and, especially, automated driving, the behavior of the system in real driving conditions is very important because these are safety-relevant systems. Therefore, it is important to prioritize the prevention of gaming of tests in this area. UNECE Regulation 79 Revision 4 [46] makes a first step in this direction by defining, among other things, the test cases for the Lane Keeping Assist (LKA). However, not all concrete test scenarios are explicitly defined. The logical scenario is defined in which the vehicle approaches a curve, where the lane shall have a clearly visible lane marking line on both sides. The test is passed if the vehicle does not cross a marking line during the test. In addition, paragraph 3.2.1.3 of Annex 8 [46] states: "the vehicle manufacturer shall demonstrate to the satisfaction of the Technical Service that the requirements for the whole lateral acceleration and speed range are fulfilled." This means that the technical service can define and test any combination of lateral acceleration and speed as a concrete scenario. It is not only within UNECE that the definition of exclusively standardized tests is avoided. In its Federal Automated Vehicles Policy [47, p. 77], the NHTSA also clearly opposes the exclusive use of standardized tests.

While today the UNECE Regulation 79 specifies a variation of two parameters (lateral acceleration and speed) for the LKA, the number of parameters to be varied will continue to increase with higher degrees of automation. It is conceivable, for example, that legislation (e. g., UNECE Regulation) will only define logical scenarios (e. g., cut-in) for the type approval of automated vehicles. During the certification process of the automated vehicle, the manufacturer and technical service have to find all relevant concrete scenarios of the predefined logical scenario by varying all possible parameters from the five-layer model introduced in the previous section. This gives the technical service the chance to adapt the concrete test cases towards the system's individual weaknesses. Additionally, this prevents performance optimization towards standardized tests, the so-called gaming of tests.

Research objective

The last sections revealed that it is important but difficult to reduce the number of test cases for the safety assessment and certification of automated vehicles. To achieve this, a system-specific derivation of relevant test scenarios is advantageous. None of the approaches stated above explicitly include system-specific properties, and therefore this kind of approach is lacking from the current state of the art. In addition, the method developed is intended to prevent the so-called gaming of tests in the certification process, ensuring the safety of automated vehicles even under real traffic conditions.

The aim of this paper is to propose a novel method of including system-specific characteristics for an efficient and individual scenario selection during the certification process of automated vehicles conducted by a technical service.

METHODOLOGY

This section describes in detail the overall procedure used, from the required input, to the method to the generated output. An overview can be found in Figure 2.

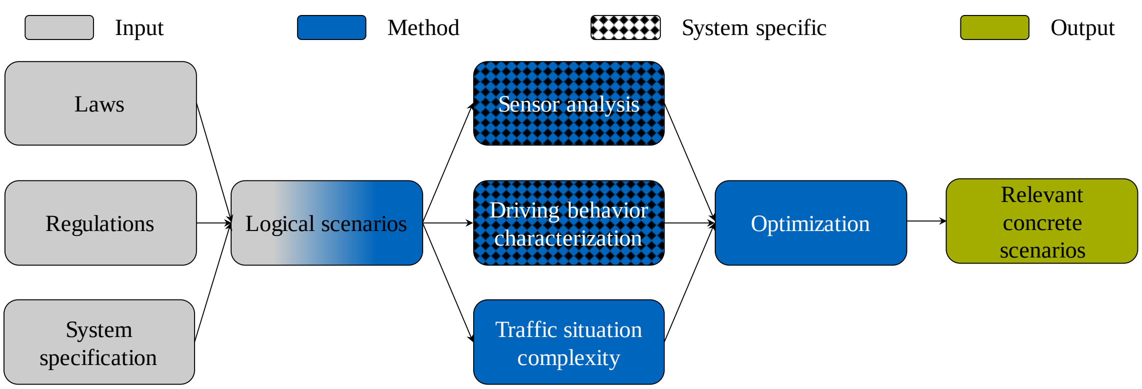

Figure 2. Overview of the procedure developed. Logical scenarios are assigned both to the input and to the method, because these are partly specified in regulations and in these cases, they serve as input.

Summary of presented approach

The starting point of the methodology developed is logical scenarios defined in laws and regulations. From each predefined logical scenario, an infinite number of concrete scenarios can be generated by a theoretically infinitely fine discretization of the parameters. The aim of the method is to restrict the parameters of the logical scenarios in such a way that a technical service can efficiently identify the most relevant test cases for the certification of the automated vehicle. This results in two special requirements for the procedure. On the one hand, it should be system-specific so that different versions of various manufacturers can be addressed efficiently. On the other hand, it should be able to work without using the driving function to be tested as far as possible, because the technical service will not usually have access to the software. What will be available to the technical service is a system specification of the SUT. The information contained therein is used in the further course of the approach.

The parameters of the logical scenarios are determined by optimization, based on the three main elements of the concept. These elements are the analysis of the sensors, consideration of the driving behavior and integration of complexity. The first two elements are specially adapted to the identified weak spots of the SUT, and thus enable a system-specific definition of relevant scenarios. The predefined logical scenarios contain only a simple description of a scenario that is suitable for demonstrating certain basic skills. For example, in a cut-in scenario, only one vehicle is defined that performs a lane change into the lane of the SUT during the course of the scenario. In order to give the scenario a certain degree of difficulty, system-independent complexity is integrated in the scenario in the final step by defining further TPs. In the optimization, all three elements must be considered in parallel. The result will be relevant concrete scenarios that are adopted towards the SUT weaknesses, which are used by the technical service for the certification process. Below, each step of the method is explained in detail.

Input

Laws, regulations and a system specification are required as input for the approach developed and will be explained in more detail below.

Laws If an automated vehicle performs the driving task, the system also takes responsibility for the actions performed. Consequently, the actions of the automated vehicle must comply with the applicable laws. In Germany, for example, these may be the Road Traffic Act (in German: Straßenverkehrsgesetz (StVG)) or the Road Traffic Regulations (in German: Straßenverkehrs-Ordnung (StVO)), which define, for example, the minimum safety distance from the vehicle in front, or maximum speeds on certain types of road. The applicable laws can be explicitly tested in a scenario, or at least considered in the evaluation of the tests carried out.

Regulations Referring back to the LITERATURE REVIEW AND RESEARCH OBJECTIVE section, certain regulations must be complied with for type approval. For the European market, these are the UNECE regulations, which represent the central aspect in the considered use case of the approach developed. Like already discussed, the UNECE regulations no longer define all tests in detail, but provide a certain framework for the tests to be carried out, which may also implicitly mean logical scenarios. Furthermore, the system manufacturer and the technical service are assigned an increasingly higher responsibility, because they have to verify that the defined requirements are met over the entire operating range. This, in turn, gives the technical service the opportunity to define all scenarios that it considers relevant for the system to be tested as definite test cases during the certification process.

System specification In the future, the number of automated systems with different functional capabilities will continue to increase. For example, there will be a wide variety of systems for the highway domain. These will differ in terms of whether special situations, such as construction sites, ramps and exits etc., can be handled by the automated driving function. In order for the selection of the logical scenarios to be tested to be as effective as possible, a system specification with the definition of the system boundaries must be available to the technical service. The system boundaries can also be used to generate test cases where the system boundaries are exceeded. The SUT also has to achieve a safe state in these scenarios. In addition, the technical service must be informed of both the sensors used and their installation position. All in all, the type and level of detail of the information provided by the manufacturer in the system specification must be such that, on the one hand, the technical service has sufficient information available for the relevant scenarios to be selected reliably and, on the other hand, the manufacturer does not have to reveal too much manufacturer-specific data in order to protect internal know-how.

Logical scenarios If logical scenarios are already defined in applicable regulations, these can be used as input for the developed approach. It may also be possible that further logical scenarios are required for the method, for example to test system functions or compliance with road traffic laws, which are required in the regulation but for which no logical scenarios are defined. An example could be that the UNECE specifies that speed limits must be observed by the system but does not specify a framework in which the tests are to be carried out. For the reasons described, the logical scenarios in Figure 2 are assigned to both the input and the method. Requirements can also be specified in the regulation without a logical scenario being defined for the verification of these requirements. This may require the technical service to define further logical scenarios during the type approval process. It is also conceivable that a scenario is only described in linguistic terms and is therefore, by definition, a functional scenario. In this case, the corresponding logical scenario must also be defined by the technical service.

Output

The output of the presented approach is represented by relevant concrete scenarios for the type approval of automated vehicles. All scenarios required to prove compliance with the requirements (e.g., by UNECE) are considered relevant for testing. The unique selling point of the developed procedure is a system-specific adaptation of the relevant scenarios to accommodate possible weak points of the system to be certified.

Method

The following explanations of the methodology blocks shown in blue in Figure 2 outline how the output described here is generated from the input described above.

Sensor analysis The perception sensors of an automated vehicle have the objective of collecting information about the environment of the vehicle, which is an important part of the driving task. Only if sufficient information about the environment is available, a safe planning of appropriate actions of the automated vehicle is possible. Not only sufficient information needs to be available, but it must also correspond to reality. Currently, in the automotive sector, the perception sensors mainly used are Radar, Lidar, camera and ultrasonic. Each of these sensor types has its own advantages and drawbacks. In order to enable the driving task to be performed safely, the various sensor types are therefore combined, and the information obtained from them is fused. For the sake of simplicity, perception sensors are simply referred to as sensors in the following.

The resulting sensor costs have a major influence on the choice of the number and type of sensors installed, especially in mass production vehicles. Furthermore, there may be restrictions due to the package. Consequently, every vehicle manufacturer will use an individual sensor setup. The goal of this section is to formulate a method for a structured analysis of the sensor setup used and to identify its weaknesses. This is particularly relevant for technical services in type approval, because they have to efficiently test vehicles from different vehicle manufacturers with different sensor configurations. In addition to the ODD (e.g., motorway or urban area) of the vehicle under consideration, the type and number, as well as its installation position and pose, also play a critical role. In the following section, the most important influencing variables of the sensors are examined in more detail. All this data must be specified by the manufacturer in the system specification for each sensor.

1) **Field of view:** The field of view describes the visual area of a sensor and is influenced by the following properties:
    a. **Range**: The different sensor types have widely-varying ranges. Ranges vary from a few meters with ultrasonic to several hundred meters with radar sensors. Different ranges also occur within the same sensor type, for example with camera sensors. While the range only has a secondary role in inner-city operation, it is a decisive factor in the use case of the highway pilot, due to the high speeds.
    b. **Opening angles:** One can differentiate between the horizontal and vertical opening angle. Both the horizontal and vertical opening angles are particularly important for detecting the vehicle's immediate surroundings. Large opening angles can reduce or even eliminate blind spots between the mounting positions of the sensors, and improve the detection of low-lying objects. As the distance from the vehicle increases, the importance of the vertical opening angle decreases, because only a relatively narrow area of the environment is relevant in the vertical direction. Only with Lidar sensors, which usually have a small vertical opening angle, does this have to be taken into account at higher distances. For example, when braking strongly, a pitch angle can occur that shortens the range of the Lidar sensor.
    c. **Mounting position:** The mounting position influences the field of view of the sensor. In general, high mounting positions are advantageous, because, in particular, objects at great distances can be detected better. In addition, sensors with high mounting positions are better protected against damage. These can be, for example, contamination by whirled-up dust and dirt, parking bumpers and similar.
    d. **Orientation:** In addition to the mounting position, the orientation of the sensors is also relevant for the field of view. Sensors pointing slightly downwards can be used primarily to cover the immediate

surroundings, whereas sensors for the more distant surroundings tend to be oriented almost horizontally.

2) **Quality of data:** The quality of the recorded data is not always the same and varies depending on the following factors:
    a. **Type**: As already mentioned, camera, Radar, Lidar and ultrasonic sensors are mainly used in the automotive industry. These sensor types have different strengths and weaknesses due to their physical principle.
    b. **Performance attributes:** The performance attributes of the sensors used must be evaluated in detail. These attributes include, for example, the cycle times of the measurement data acquisition, which can provide information about the minimum reaction time of the system. In addition, sensor type-specific information, such as the transmitted power of the Radar or the number of pixels of the camera used, may be of interest. The latter, for example, provides information about the achievable depth of detail of the recorded sensor data.

Considering the interaction of all the factors shown, the sensor setup used can be examined. In the first step, the ideal sensor coverage of the system is investigated. This requires influencing factor 1), which is explained above. "Ideal" in this context means that all objects within the field of view of the sensor are correctly detected. This makes it possible to conclude not only whether and where the sensor setup shows blind spots, but also which areas are covered by several sensors or even several sensor types. From blind spots to multiple sensors to multiple sensor types, the probability of correct detection and classification of objects generally increases.

In the second step, phenomenological sensor models based on influencing factors 1) and 2) are used to study sensor coverage at greater distances from the SUT. These extend the ideal sensor models used previously by modeling individual phenomena, such as attenuation due to weather influences or the decrease of the signal received with increasing distance from the object. Phenomenological models, therefore, have a higher information content, but also require more computing resources. For completeness, reference is also made to physical sensor models that simulate the physical effects of the sensor and, thus, best represent reality. One example is so-called ray-tracing methods, which do, however, require enormous computing capacities and are therefore not practicable for the desired purpose. Phenomenological models, on the other hand, represent a good compromise between information content and required computing capacity.

With the phenomenological sensor models used, it is possible to investigate whether there are not only areas in the far field of the SUT that are not within the detection range of the sensors, but also areas in which the detection probability is poor. It is also possible to investigate whether any prevailing weather conditions are particularly critical for the sensor setup to be investigated. Road topology may also have an influence on the probability of an object being detected. Depending on the characteristics of the sensor setup under consideration, other curve radii, longitudinal slopes, or hilltops and valleys may pose special challenges for the SUT.

This investigation is particularly interesting for systems where the highway is part of the ODD. With the procedure described, environmental conditions, such as critical curve radii or weather conditions, can be identified, thus reducing the number of relevant scenarios. A further reduction of the number of scenarios is the adaptation of the trajectories of the other traffic participants. The trajectories can be optimized in such a way that the traffic participants approach the SUT in areas where the detection probability is as low as possible.

An extension of the sensor analysis is the inclusion of the sensor data processing, which allows the entire module of the perception to be considered. A detailed insight into the data processing software will not be available to the technical service, but it is still possible to include known state-of-the-art weaknesses in the adaptation of the tests. According to DIETMAYER [48], errors that can occur in the perception are assigned to the following three categories:

1) **State uncertainty:** Deviations between the measured state variables (such as position or speed) and those that are correct.
2) **Class uncertainty:** The classification of the detected object is incorrect. One example is the classification of a motorcycle as a cyclist.
3) **Existence uncertainty:** An existing object is not detected, or a non-existent object is incorrectly detected as an object (ghost object).

The technical service cannot accurately predict the occurrence of these errors, but the current state of the art can be used to identify situations in which the probability of one of the three error types occurring increases. For example, it is known that Radar sensors have problems in detecting stationary objects. This information can be taken into account when creating concrete scenarios.

In summary, the objective of analyzing the sensor setup used is for the technical service to adapt the given logical scenarios. This enables concrete test cases that address the identified weaknesses of the SUT's sensor setup to be selected efficiently for certification.

Objective characterization of driving behavior The aim of the objective characterization of the driving behavior of the automated vehicle is to identify systematic weak points in the driving behavior, so that the scenarios used for type approval can be adapted accordingly. This should be possible by means of a limited number of functionality-based tests carried out in advance in special scenarios, so-called characteristic situations. An example of this is the curve driving behavior of the system, which can be investigated beforehand. There may be systems that tend to drive on the inside of curves and others that have a more outside tendency. This information can be used, for example, to adapt cut-in situations in curves specifically to the side where the automated system is more likely to drive. If it drives on the inside of a turn, a vehicle cutting in from the inside direction is more relevant for this vehicle, because the lateral distance between the vehicles tends to be smaller.

A structured approach is required to ensure that all the necessary information can be obtained efficiently. Figure 3 gives an overview of the procedure used. Information sources are displayed in gray, the generated situation catalog in blue and the further utilization in green. Most of the information sources used are state-of-the-art and are already known, at least for manually controlled vehicles. The novelty of this approach is the transfer to automated vehicles and the further use of the information acquired for their safety assessment.

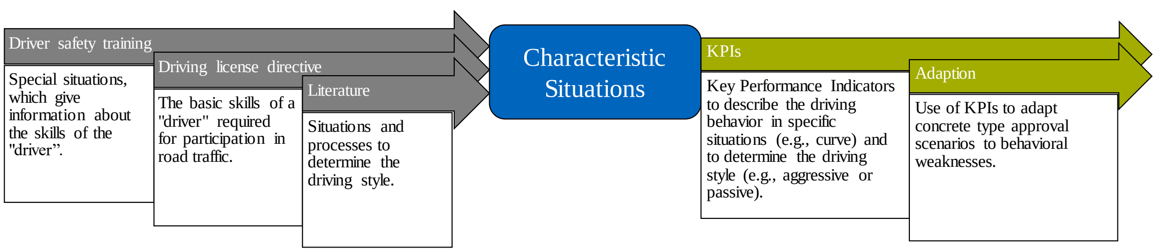

Figure 3. Developed approach for an objective characterization of SUT's driving behavior

In driver safety training courses, the driving skills of human drivers are tested in particularly difficult situations, some of which do not appear or occur extremely rarely in real road traffic. Nevertheless, some tests of driving safety trainings can be used to make a statement about the "capabilities" of automated vehicles. For example, the behavior of the automated vehicle at low coefficients of friction can be investigated.

In Germany, the Driving License Directive defines the minimum requirements that a person must meet in order to be allowed to actively drive a vehicle in road traffic. Not all requirements (e.g., correct adjustment of the side mirrors before driving) can be transferred to an automated vehicle. However, the practical driving test does include some requirements for behavior that can also be applied or transferred to an automated vehicle. These are applicable if the driving examiner drives the automated vehicle in real road traffic and can, at some effort, be transferred if they are carried out in simulation and the requirements of the driving examiners have to be objectified and automated. In addition, the theoretical exam contains a category of questions on how to behave in certain sample situations. These are currently being shifted into theory because the probability of these situations occurring is relatively low. When automated vehicles are tested, these types of tests can be transferred to simulation, and the correct behavior of the vehicles can be tested. From this, it can be concluded that, in addition to the accident-free handling of the type approval tests, the "functional" requirements of the Driving License Directive must also be considered and continuously checked. These types of scenario represent relevant scenarios that do not necessarily have to be critical or complex.

Existing literature can be used to determine the driving style. Studies have already been carried out to determine the driving style of both human drivers [49] and for automated vehicles. Comparisons have also been made between manual and automated driving, such as in [50]. Abnormal behavior (whether aggressive or defensive) can lead to increased risk in the interaction between human drivers and automated vehicles. Hazards occur when the behavior of an automated vehicle does not match the response expected from human drivers, which may be due to inadequate communication between the driver and the automated vehicle. In order to identify this type of risk and integrate it into the further course of the type approval process, it is advisable to use the Systems-Theoretic Process Analysis (STPA) [51] risk analysis method. This method is particularly suitable because it examines the interaction between complex systems as the cause of errors. The individual systems themselves can operate error-free. Applied to our use case, this means that neither the automated vehicle nor the human driver behaves incorrectly, but their interaction nevertheless leads to risks.

Combining the knowledge from the three information sources shown, a catalog with characteristic situations can be created. If these are carried out in a real test or simulation, key performance indicators can be evaluated that reflect the driving style and weaknesses in driving behavior. This information can then be used for the further type approval process by adapting all future test scenarios to suit the weaknesses identified in the vehicle's driving behavior. For this part of the method, the driving function is required for a limited number of tests. If this is not available, the overall method is still applicable - however, the efficiency in selecting the test cases decreases.

Complexity The aim of this section is to design the concrete scenarios for the type approval of automated vehicles as complex as possible. For a better understanding of the distinction between complex and critical scenarios, we refer once again to the 'Definition of vocabulary' subsection. In future regulations (e.g., UNECE), logical scenarios will be defined that confirm that functional requirements for the system to be tested are fulfilled correctly. One example of this could be the possible logical scenario "object in the SUT's lane", in which the automated vehicle must react appropriately to an object in its lane. In [52], the functional requirement for this logical scenario is that the vehicle must be able to avoid the object by means of braking, steering or a combination of both. Analogous to the currently applicable UNECE R79, which requires proof that the Lane Keeping Assist can be transferred to general situations, this will also be required here. Adding complexity to traffic situations represents an essential component in the transfer to general situations in which an object is located in one's own lane.

The procedure described here should, therefore, be used to introduce a general system-independent difficulty to the given, simple logical scenarios. This is accomplished by adding complexity to the given logical scenario. In general, complexity can be caused by components of all five layers, according to BAGSCHIK [11]. For example, a change in the sign of the lateral slope of the roadway (roadway twisting), which is assigned to layer one of the five-layer model, can represent a particular complexity for the lateral guidance of the vehicle. Consequently, all five layers must be examined separately. This paper limits itself to layer four (objects). Objects are used here as an overarching term for obstacles and other road users of all kinds. Objects can, therefore, be stationary or movable. Due to the limitation to layer four, complexity is understood in this publication as the difficulty faced by the planning algorithm in planning a safe trajectory resulting from the movement or presence of objects.

According to BACH [53], no abstract definition of complex situations for automated vehicles has yet been determined. One approach is offered by SCHAUB [54], who has defined eight criteria for complex situations in which people have difficulty making decisions. In his work, SCHULDT [55] examined how these criteria can be transferred to the complexity of traffic situations for automated vehicles in theory, and concludes that they are also adaptable to this application. The complexity criteria defined by SCHAUB [54] and confirmed by SCHULDT [55] for automated vehicles are as follows:

- Number of elements
- Number of states per element
- Interdependency
- Self-dynamics
- Intransparency
- Multiple conflicting goals
- Openness of the target situation
- Novelty

For a detailed description of the meaning of each criterion in relation to complex traffic situations for automated vehicles, see Chapter 2 in SCHULDT [55]. It is not possible to use these characteristics directly to create complex scenarios, because they only exist in verbal form so far. In addition, the characteristics are used to evaluate existing scenarios and not to generate new ones. A further aspect that impedes direct use is the fact that the evaluation has so far only been carried out subjectively. This is not sufficient for the procedure developed here, because an automated optimization of the scenarios is conducted in the next step.

In order to apply the criteria for describing complexity that exists in literature, four main points need to be analyzed. The procedure is summarized in Figure 4. First of all, it is necessary to ascertain whether further criteria are required to generate the scenarios carried out here. This can be accomplished by defining a list of requirements and comparing the extent to which the existing criteria meet all of them. Secondly, an evaluation must be performed to determine whether the characteristics have a certain upper limit. The number of the involved elements (objects) is theoretically not limited, but due to the physical allocation only a limited number of objects are important for executing the driving task. The number of objects to be considered must be examined in order to apply the presented method efficiently. Thirdly, the criteria that were previously only defined verbally must be described mathematically in order to be usable for the subsequent optimization. Finally, the objectified attributes must be validated using simulations and real driving data. Since complex scenarios do not necessarily have to lead to a critical outcome of the scenario, special key performance indicators are necessary for validation. A parameter that could be used for the validation is, for example, whether the automated vehicle changes its decision about the actions to be performed during the scenario. If the vehicle starts to dodge an object on the left and then decides to dodge it on the right, this is an indication of a complex scenario, even if the outcome of the scenario is not critical.

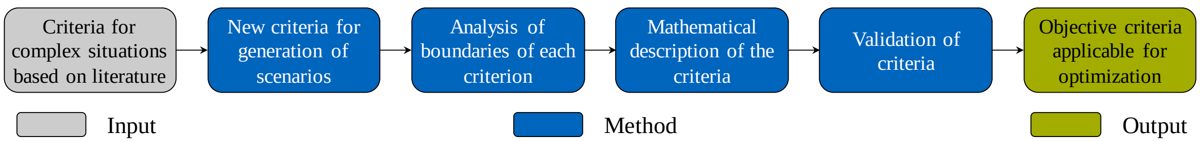

Figure 4. Approach for the definition of an objective complexity metric.

Optimization In the last step of the developed methodology, the individual components previously described are integrated. For this step, the driving function to be tested does not have to be available. The starting point is an arbitrary logical scenario, which is prescribed in the regulation under consideration. The aim is to adapt or select parameters of the logical scenarios that BAGSCHIK [11] defines in a five-layer model in such a way that relevant concrete scenarios are derived from the given logical scenario. Each of the three methods described in detail above contributes to the determination of specific parameter values within the five layers, which is described below and summarized in Table 1. The temporary manipulation of L1 and L2 (L3) represents unusual traffic situations, such as a changed lane routing marked by pylons within a temporary construction site. These special situations are not the focus of this work and will not, therefore, be considered further.

Table 1. Considered influence of the individual aspects on the determination of the parameters of the five-layer model according to BAGSCHIK [11].

	L1	L2	L3	L4	L5
Sensor analysis	✓	✓	✕	✓	✓
Driving behavior	(✓)	(✓)	✕	✓	(✓)
Complexity	✗	✗	✕	✓	✗

Influence: ✓ high (✓) weak ✗ none ✕ neglected

Sensor analysis: The sensor analysis can be used to determine parameters from all four considered layers of the five-layer model. For optimization, the relationship between the individual layers must be taken into account. If, for example, obstructions are taken into account, the position of objects (L4) can have an influence on infrastructure elements such as traffic signs (L2). In addition, connections also exist between complexity and sensor analysis. Sensor analysis identifies areas in which the probability of detection is low. In the subsequent optimization of the complexity, the trajectories of the objects are calculated in such a way that the scenario is as complex as possible, and the potential conflict partner is located, as far as is possible, in the previously-identified areas with weak sensor coverage. A potential conflict partner is the object that forces the SUT to act. Thus, an object in its own lane can be the potential conflict partner forcing the SUT to avoid or brake.

Driving behavior: The influence of the identified driving behavior on the optimization of the parameters is evaluated as weak for most layers. Thus, in Road-level (L1), the analysis of driving behavior cannot determine which exact curve radius is of particular importance for the system, but it can conclude whether the system tends to drive through curves more on the inside or outside. This information can then be used to adjust the position of the potential conflict partner from layer four (objects) within curves.

Complexity: The parameters of the fourth layer (objects) can be determined by systematically introducing complexity. As mentioned before, other layers can also contribute to increasing complexity, which is neglected in this paper. The definition of complexity is defined here as the complexity of the motion and presence of objects. Here, the connection to both other aspects is given by calculating the trajectories of the objects in such a way that they address not only the complexity but also the sensor deficiencies, as well as the identified driving behavior. While the two previous steps are mainly limited to the trajectory of the conflict partner, the optimization of complexity also focuses on defining further objects and their optimal trajectory.

All in all, this results in a two-stage procedure in which the parameters of layer one, two and five are first optimized by sensor analysis and consideration of driving behavior. In addition, the trajectory of the potential conflict partner (L4) is determined. In the second step, further objects are defined by considering complexity and their trajectories are optimized. Therefore, two consecutive optimizations are carried out, each with a suitable algorithm. Especially in the second optimization step, a multi-objective optimization (Pareto optimization) can be of significant importance due to the competition of multiple factors of complexity.

The definite cost function for the first optimization step will vary from system to system, because these two aspects have the very objective of finding system-specific weaknesses. Since the result influences the second optimization step, these results will also be dependent on the SUT. In addition, when optimizing the parameters and, in particular, when optimizing the trajectories of the objects, it must be ensured that certain constraints are met. For example, there must be enough space for the SUT that it is physically able to cope with the scenario without causing an accident, meaning that so-called dilemma situations are not considered. In addition, the trajectories of the objects or the other TP must be physically possible. Depending on the type of TP, approximations such as a simple point mass model, the circle of forces or a single-track model can be used.

The optimization method presented results in more than one relevant concrete scenario from the given logical scenario, due to the applied multi-objective optimization. To execute these scenarios efficiently, simulation is suitable, in which the required parameters - in contrast to test site tests - can also be set without major expense.

RESULTS

This chapter shows an exemplary elaboration of the concept using a driving function designed for the ODD highway. The individual blocks of the approach shown in Figure 2 and the resulting concrete scenario for the example function are explained.

The input of the exemplary results shown here is a fictive system description including the used sensors and a draft of a regulation[2] for the certification of automated vehicles. Within this fictitious regularity, the logical scenario "avoidance of a stationary obstacle" is defined, which represents the starting point for the individual steps of the method. The purpose of the predefined logical scenario is to show that the SUT has the principal functionality needed to avoid a stationary obstacle. A schematic sequence of the scenario in its simplest form is shown in Figure 5 on the left-hand side. The SUT drives in the right lane of a two-lane highway and detects a stationary object with its sensors. Detection takes place at an early stage due to the unrestricted view. Since the adjacent lane is not occupied, the SUT can change lanes and drive past the stationary object with sufficient side clearance. The successful handling of this scenario can be understood as the fulfilment of the functional requirements mentioned above. If, analogous to the existing UNECE R79, the technical service, in cooperation with the manufacturer, is required to prove that this capability can be transferred to general situations (here: general evasive situations of a stationary obstacle), the methodology developed can be used to define system-relevant concrete scenarios that are not previously known to the manufacturer.

[2] Proposal in UNECE 'Working Party on Automated/Autonomous and Connected Vehicles (GRVA)' informal working group 'UN Task Force on Automated Vehicle Testing (AutoVeh)' [52]

The following paragraph explains how the optimized relevant scenario (right-hand side of Figure 5) can be identified systematically using the method presented. In the optimized scenario, the SUT's view of the stationary object is restricted by a curve on the one hand, and by another TP on the other. Since the object was detected at a late stage, it is no longer possible to brake to a standstill in front of the object. The SUT must switch to the left lane to prevent an accident. This lane is blocked by other vehicles moving at slightly higher speeds than the SUT. The SUT must brake to avoid colliding with the object, but cannot brake too much, in order to avoid a risk to TP 3 when it changes lanes into the gap between TP 2 and TP 3.

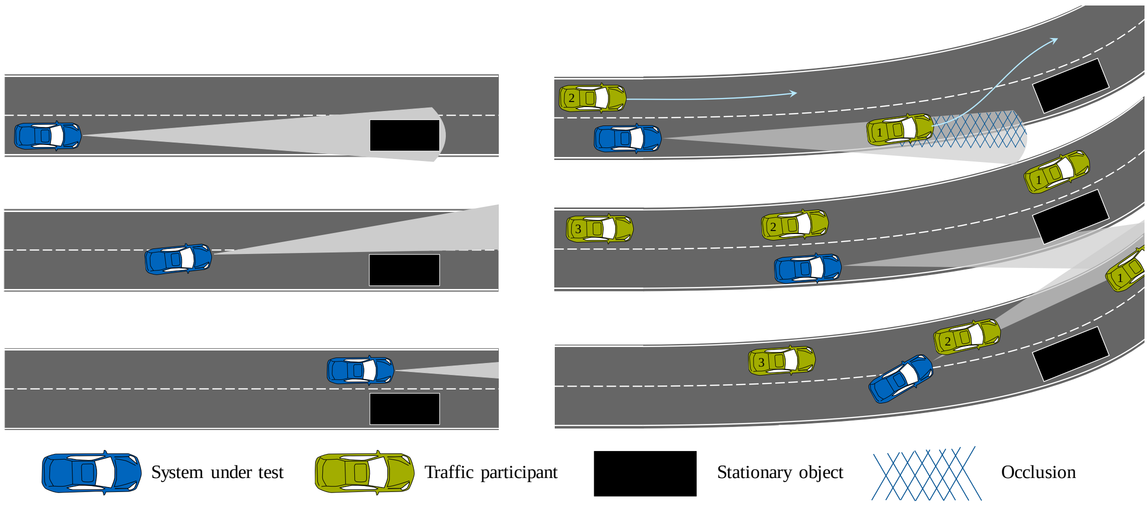

Figure 5. Logical scenario "avoidance of a stationary obstacle" in its basic version (to the left) and in an optimized version (to the right).

Sensor analysis: Using the system specification, disadvantageous Road-level (L1) parameters for the sensor setup used can be determined. In the example shown here, this is a curve with a certain radius, which means that the sensors used can hardly see the course of the road. In addition, the sensor analysis defines another TP (L4), which increases the occlusion of the stationary object. The distance between the SUT and the TP is defined on the basis of the opening angles of the sensors used, so that optimum occlusion of the stationary object is achieved during cornering. In addition, the environmental conditions (L5) can be selected in the scenario (no environmental conditions are shown in Figure 5, with the result that the operational weak points of the sensors used are taken into account. In a system that mainly uses cameras, this can be direct sunlight from the front.

Driving behavior: Characteristic tests carried out in advance show that the SUT tends to use the outer side of curves for orientation. Therefore, in the scenario under consideration, a left-hand curve is chosen because the lateral distance of the SUT to a safe position is then maximized. Instead of testing both left-hand and right-hand curves, this method allows a well-founded selection of this parameter.

Complexity: In the last step, system-independent complexity is added to the scenario on the basis of the criteria of SCHAUB [54] and SCHULDT [55]. For example, the number of elements is increased (definition of further TPs). The trajectories of this TP are adapted in such a way that they increase the number of actions required by the SUT to achieve a safe state, for example by representing restrictions on action. In the specific example, in order to successfully pass this scenario, the SUT has to brake in a controlled manner and reeve into a gap between two vehicles traveling at different speeds, because braking to a complete standstill is no longer possible without colliding with the stationary object. As already explained in the subsection ‘Definition of vocabulary’, the speed of the TP and the starting speed of the SUT are also increased, and distances between the TPs are reduced in order to increase criticality. In addition, a connection to the sensor analysis is made so that the other TPs stay as long as possible in areas with low sensor coverage or even in blind spots that are not visible to any sensor.

From the technical service's point of view, this scenario is relevant for the SUT to be tested and should, therefore, be taken into account when the SUT is certified. This can support the required proof of transferability of the capabilities to general situations in which an object must be evaded in its own lane. At the same time, it is difficult for the manufacturer to prepare for the tests, due to the individual adaptation of the scenarios, and thus so-called gaming of tests is prevented, and the safety level achieved during certification can be transferred more effectively to real driving conditions.

For simplicity's sake, this example does not discuss all parameters that can be determined by the optimization. For example, further parameters of the road geometry can be adapted to the weak points of the SUT sensors. Even if not all parameters are explained, the example shows very clearly which results are achieved with the developed method.

DISCUSSION AND LIMITATIONS

This section critically discusses the developed approach. This concept has been specially developed for the type approval process of automated vehicles. As indicated in the section LITERATURE REVIEW AND RESEARCH OBJECTIVE, the focus is on Object and Event Detection and Response (OEDR), and therefore not all tests required for type approval are addressed. One of the basic assumptions of this paper is the specification of logical scenarios for type approval by legislation. This assumption is justified because UNECE already has existing regulations for ADAS according to this principle, and UNECE working groups already have initial proposals [52] for automated vehicles that also work with the definition of logical scenarios. In addition, large research projects, such as PEGASUS (highway) [2] and CETRAN (urban) [56], also work with the definition of logical scenarios.

With the method presented, it is not possible to determine all parameters of the five layers model precisely, because it is not entirely possible to determine the relevance of a parameter for a scenario. For instance, even after the methodology has been applied, it is unclear whether the type and shape of the central lane marking in the scenario in Figure 5 has an effect on the outcome of the scenario. Consequently, a parameter variation must still be performed in simulation. However, the extent of this variation is significantly reduced by the parameters that have already been defined. Despite constantly increasing computing power, it is important to keep the number of necessary tests in simulation low, because high-precision simulation models with considerable computing costs must be used for a meaningful simulation-based test of the overall system. The presented method thus has an advantage compared to the exclusive criticality optimization through simulation execution, because no additional prior knowledge is included in the latter. Using this prior knowledge, edge cases can be identified more efficiently with the novel method presented. In addition, the procedure presented here can largely be carried out without the actual driving function, which is of great importance for a technical service. The actual driving function is only necessary for a limited number of tests in order to determine the driving behavior. As stated in the subsection ‘Objective characterization of driving behavior’, if the driving function is not available, the overall method is still applicable - however, the efficiency with which test cases are selected decreases.

As with all methods for selecting and reducing scenarios described in the subsection ‘Scenario selection and reduction methods’, the method developed does not cover the entire parameter space. Therefore, there is no guarantee that all errors of the SUT will be detected. Finding as many faults as possible is of great importance for the system manufacturer in terms of product liability. The situation is different for a technical service when it comes to system certification. The main purpose of the type approval is to test relevant scenarios under given framework conditions by regulations. The technical service must ensure, with minimum effort, that no relevant error cases remain undetected and that the SUT conforms to the applicable regulations, which is achieved with the developed approach.

It is also possible to combine the method with existing methodologies for scenario selection. For example, it can be combined with the use of critical accident scenarios from a database. An accident stored in the database can be considered as a logical scenario to which the developed methodology can be applied. Thus, it is possible to show whether the SUT can prevent existing accidents even under disadvantageous conditions.

CONCLUSION AND FUTURE WORK

This paper presents a novel and advanced method for defining relevant test cases for the future type approval of automated vehicles. The method is specifically adapted to the requirements of a technical service performing type approval. Based on regulations currently under development, such as UNECE and other laws to be complied with, scenarios relevant to the system under test are identified. As with existing UNECE regulations (e.g., for the Lane Keeping Assist), it can be assumed that not all tests are specified in detail in the regulations, but only in the form of logical scenarios. This enables the technical service to carry out scenarios that are relevant from its perspective, thus preventing so-called gaming of tests, and at the same time perform an efficient evaluation of the vehicle to be tested.

The methodology presented is essentially based on three pillars: analysis of the sensor setup used, inclusion of driving behavior and consideration of complex traffic situations. In the first two steps, system-specific weaknesses of the system to be tested are identified. In the third step, the logical scenario given by the regulation is extended to include a complex traffic situation in order to challenge the planning algorithm of the vehicle. After a final optimization, in which the three mentioned sub-methods are combined, the concrete scenarios relevant for type approval are obtained.

The methodology for the analysis of the sensors is partly available and will be continuously improved in further work. A comprehensive analysis is currently being carried out for the characterization of driving behavior to determine what information on driving behavior can be included in the future type approval process for automated vehicles. In the future, the methodology for integrating complexity into the tests to be performed will be developed. To achieve this, linguistic definitions of complexity from existing literature will be analyzed and transformed into a mathematical form. Subsequently, a validation of the complexity will be carried out by means of simulations and real driving data. Finally, the complexity can be included in the optimization. If all three components described are available, the optimization can be carried out in a final work and the total method can be applied to a real system as well as being validated.

ACKNOWLEDGEMENT AND CONTRIBUTIONS

The work for this paper was funded and supported by TÜV SÜD Auto Service GmbH. Thomas Ponn (corresponding author) initiated and developed the main parts of this paper. Christian Gnandt provided essential scientific background information regarding the safety assessment of Advanced Driver Assistance Systems and Automated Driving. 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. The author would also like to thank Alexander Schwab for the critical and productive discussions on how to characterize the driving behavior of automated vehicles objectively.

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Assessment of Technical Requirements for Level 3 and Beyond Automated Driving Systems Based on Naturalistic Driving and Accident Data Analysis

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Paper Number 19-0280

ABSTRACT

Automated driving systems of SAE Level 3 and beyond allow transferring the driving task and responsibility to the vehicle and its automation systems. A crucial challenge for development and real-world performance is the balance between functionality, availability and safety, as a human driver only needs to be available as a fallback after sufficient lead-time. Consequently, automated driving requires enhanced capabilities of sensors, algorithms and actuators. This paper focuses on improved safety and driving comfort of automated vehicles and upcoming technical requirements compared to driver-only or assisted driving. It uses and adapts the state-of-the-art prospective effectiveness assessment method of ADAS to estimate accident avoidance potentials of automated driving systems. The data sources for this analysis are the Strategic Highway Research Program 2 (SHRP2) and the German In-Depth Accident Database (GIDAS). Exemplary automated driving functionalities for highways are prospectively evaluated and the impact on both traffic safety and driving comfort are presented using crash, near-crash and baseline data. Furthermore, relevant technical requirements for corresponding automated driving systems are derived. For an exemplary use-case, possible impacts on system functionality, availability and safety are presented. Additionally, safety potentials of installing high-performance sensors for automated systems of Level 3 and beyond when driving manually are discussed.

INTRODUCTION

In literature, there are different approaches to define automation levels. Internationally, SAE J3016 [Sae18] is among the most prevalent, and thus used in the following analysis. SAE J3016 outlines six automation levels starting from Level 0 (No Driving Automation) to Level 5 (Full Driving Automation). In this paper, system automation is defined from Level 3 (Conditional Automation) where the Automated Driving System (ADS) performs the entire Dynamic Driving Task (DDT) within the Operational Design Domain (ODD). In Level 3, the ADS sends a transition demand to a fallback-ready user to take over the DDT in the event of a system error or approaching the ODD boundary. In case the driver does not respond appropriately, the ADS might engage a failure mitigation strategy. Automated driving systems in higher automation levels (Levels 4 and 5) incorporate a system response to perform the DDT fallback.

When developing Level 0-2 systems, there are no minimum system requirements due to the instant availability of the driver as a system fallback. Thus, a bottom-up approach can be pursued. The accident prevention potential of active safety systems for manual driving is developed step-by-step addressing more complex scenarios. In contrast, for a Level 3+ automated driving system, the driver/user is not readily available as an instant fallback maneuver. Therefore, a bottom-up approach is not suitable. Using a top-down approach, a corresponding system effectiveness can be determined by restricting the ODD according to system functionalities. For this purpose, the respective system requirements must be derived from different application cases. Hence, a new development process has to be established that is not only based on crash data but also on critical situations (near-crashes) and normal driving situations (baseline).

This paper is structured as follows: to begin with, related work regarding accident prevention potential of ADS and technical requirements are discussed. In the subsequent section, a critical review of literature and research questions of this paper are presented. Section *Methods and Data Sources* introduces the applied methodology to analyze comfort and safety gain based on naturalistic driving and accident data. Section *Results* presents the impact on safety, availability and functionality for different capabilities of ADS. Finally, results and corresponding limitations are discussed and an outlook is offered.

RELATED WORK AND LITERATURE REVIEW

Enhanced safety measurements like improved passive safety and infrastructure have led to reductions in bodily injuries in high-income countries during the previous decades [Who15]. Furthermore, active safety systems such as autonomous emergency braking are increasingly being required by consumer protection, insurance organizations and regulation [Eur19], [Gdv18], [UNa14]. These kinds of systems show significant reductions in accident frequency, bodily injuries and overall losses [Doy15, Fil15, Rat15, Hld11-Hld15b].

Current safety systems, e.g. autonomous emergency braking, are contrived following a bottom-up development process (Figure 1). In this approach, the system functionality and the corresponding real-world accident prevention potential are continuously improved from rear-end vehicle-to-vehicle collision scenarios to current and upcoming functionalities like emergency braking for pedestrians, cyclists and powered two-wheelers, including junction and crossing scenarios. In order to develop automated driving systems (corresponding to Levels 3 to 5) this kind of process is no longer suitable, as the driver is not promptly available as a fallback solution. In this paper, a new approach is developed to evaluate automated driving systems of Level 3 and beyond using a top-down development process. Such a process offers an adjustment of system availability in accordance with previously established technical system requirements of certain driving scenarios.

The typical approach to define technical requirements for future safety systems includes the following steps [Wis13, Wis13a, Edw14, Sei14]:

- Accident analysis of critical real-world collisions
- Clustering and weighting of accident data to scenarios
- Deriving a test scenario and procedure based on clustered accident scenarios
- Developing, testing and real-world validation of a specific function

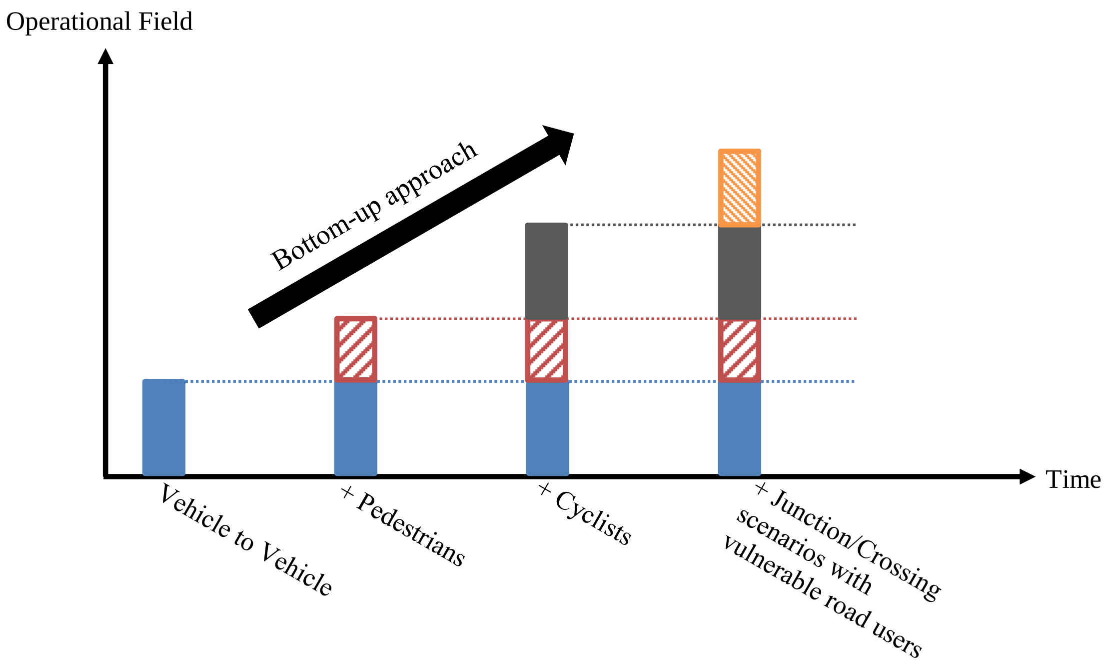

Figure 1. Schematic bottom-up approach for active safety or assistance functions

The German Insurance Association conducted an analysis regarding the impact of automated driving functions on the expected claim expenditure until 2035 [GDV17]. For that study, the monetary reduction of corresponding systems was calculated from system relevance, system efficiency, utilization rate and market penetration rate. The system relevance was determined using accident data and describes the number of crashes a system would be able to address. As not every addressable accident will be a preventable, system efficiency was defined. To take into account that the system might not be active in every driving condition and not present in every vehicle, a utilization rate and a market penetration rate was introduced. Different system functionalities and corresponding requirements (e.g. driving in unfavorable weather condition, performing a lane change etc.) can be addressed by adapting the system efficiency. However, using the method presented, a system efficiency highly depends on expert estimates. To evaluate system requirements regarding the system availability, an analysis of normal driving situation (baseline) has to be conducted as well.

With respect to system requirements of L3+ systems only generic approaches are presented in literature, for example in [Udv18]. Unfallforschung der Versicherer [Udv18] introduces universal requirements for automated driving. However, these do not permit to address the impact on system functionality, system safety and system availability.

AIMS AND OBJECTIVES

Current assessment methods for Level 3+ automation systems have a number of limitations. State-of-the-art effectiveness assessments are based on crash data. Another aspect that should be considered is the additional comfort a driver can gain from using such an automated driving system by transferring the driving task to the system. Thus, drivers' workload may be reduced. Further safety benefit is also to be expected by resolving near-crash situations. A large proportion of near-crashes would show that humans can adequately handle critical situations. These must also be addressed by a Level 3+ automation system. In order to answer these research questions, driving data is needed for baseline events in addition to crash data. As currently used databases only include crash data, an alternative database setup needs to be investigated.

Previous analyses consisted of potential assessments of generic systems without establishing system requirements. An assessment of Level 3+ systems requires a detailed analysis of system requirements for functionality, safety and availability.

This raises the following research questions:

- What is the accident prevention potential of different automated driving functionalities?
- How can the driver comfort be assessed?
- How do various functionalities affect driver comfort?

METHODS AND DATA SOURCES

The data source for our analysis is the Strategic Highway Research Program (SHRP) 2 naturalistic driving database. This data source includes 4,300 years of accumulated driving data, approximately 3,400 participants and 3,300 participant vehicles [Han16]. The study took place in six different cities within the USA. The installed data measurement system stored various time series data, like velocity or steering angle [Vtt16]. Furthermore, manually coded event data and videos of scenarios are available. In total, within the data set 1,465 crashes, 2,710 near-crashes and 20,000 balanced-sample baselines exist.

In the first step, different circumstances, such as locality, crash severity or pre-incident maneuver, are analyzed based on the available NDS SHRP2 data. In this analysis, we focus on automated driving functions for interstates/bypasses/divided highways. Streets with no separated driving directions and traffic signals are hence excluded. An accident prevention potential for a generic highway pilot is determined based on the crash and near-crash events within the SHRP2.

The next steps describe the influence of different technical requirements, their specifications and boundary conditions regarding the impact on functionality, availability and safety. As a human driver is not promptly available for redundancy, a new approach is needed and proposed in this paper. A top-down methodology is applied to determine the influence of different boundary conditions and corresponding technical requirements on the availability of an automated system (Figure 2). In each step, the top-down approach describes the influence of technical requirements on the operational design domain. As not all boundary conditions are manageable, an actual implementation will not cover the operational design domain of a generic highway pilot. Exemplary boundary conditions include:

- weather and surface conditions
- locality, e.g. highway with separated driving directions and no traffic signals
- driving velocity
- use cases, e.g. lane changes, overtaking
- traffic control, e.g. toll gates or police officers

Considering the data from SHRP2 as a baseline, an analysis can be performed whether a specific technical implementation would cover a specific scenario from the database. This allows to judge the comfort advantage of an automated driving function – "how many driving events can be covered by specific functionalities under various boundary conditions?" A similar approach can be taken to analyze the proportion of crashes and near-crashes to establish the accident prevention potential of a specific automated driving system. Thus, the balance between availability and safety has to be considered for different functionalities of a highway pilot – e.g. lane changes, entering/exiting highway or driving under unfavorable weather conditions.

If a current technical solution is not able to handle the baseline scenarios or manage existing crashes/near-crashes, the operational design domain of an automated driving system has to be successively reduced until an acceptable status has been achieved. The influence of various boundary conditions on comfort advantage or safety benefit will be shown for different system specifications of a highway pilot based on SHRP2 data.

To compare SHRP2 data with German accident data the German-In-Depth-Accident-Study (GIDAS) [Erbs08] was used to analyze accidents on German highways. The GIDAS teams have been analyzing and reconstructing approx. 2,000 accidents per year since 1999 in the vicinity of Hanover and Dresden. The advantage of this database is the availability of information about every person involved in the accident. Therefore, an analysis was conducted and required data was extracted for all passenger vehicles involved, meeting specific filter criteria. The GIDAS dataset from June 2018 was used and only reconstructed and fully coded accidents were included.

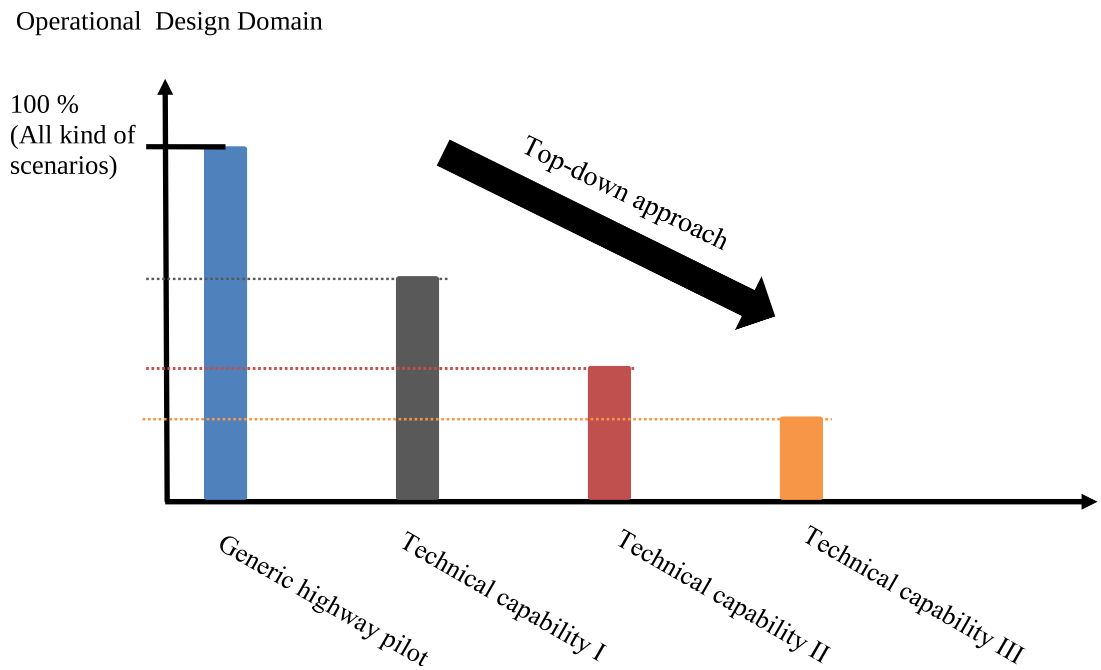

Figure 2. Top-down approach demonstrating the influence of technical requirements on the operational design domain and comfort advantage of an automated driving function

RESULTS

Within the SHRP2 naturalistic driving study, 1,465 accidents, 2,710 near-crashes and 20,000 baseline events are available. Figure 3 a) shows the relative distributions thereof for the respective localities. In this figure, localities are ordered by descending number of crashes. Nearly 48 % of all collisions (including low-risk tire strikes) occurred within business and industrial areas. However, participants only drove within these localities for 32 % of the time. In contrast, only 5 % of all collisions occurred at interstates/bypasses/divided highways with no traffic signals, where a large amount of all near-crashes (21 %) and especially baseline events (27 %) took place. Within this street type fewer collisions occurred, but a large amount of critical near-crash events were mitigated successfully by the human drivers. In addition, a high proportion of baseline events occurred on streets with separated traffic directions and no traffic signals. Consequently, a high comfort advantage may be provided with a highway pilot.
Figure 3 b) illustrates the relative proportion of crash severity under the influence of locality. More severe and police-reportable crashes occurred on interstates/bypasses/divided highways. On streets with no traffic signals but divided driving directions 26 % of crashes were severe and 25 % were police-reportable, while most accidents occurred on business/industrial streets where 12 % were severe and 17 % police-reportable.

In conclusion, on interstates/bypasses/divided highways with no traffic signals fewer accidents occur compared to localities such as business/industrial, residential or school. This result is similar to existing research for a potential safety benefit of a generic highway pilot [Gdv17]. In contrast, this NDS analysis shows that a relatively high proportion of near-crashes occurred on streets with divided traffic directions and no traffic signals. These critical events were handled well by human drivers, thus an automated system needs to perform equally well in these scenarios by avoiding such near-crashes or by predictive driving. Furthermore, collision avoidance for highways/interstates would particularly reduce severe collisions. In general, a large positive influence on critical events, on crash severity, and on accident reduction potential can be established for a generic highway pilot. For the further analyses in this paper we focus on automated driving functions for interstates/bypasses/divided highways use cases excluding streets with no separated driving directions and traffic signals.

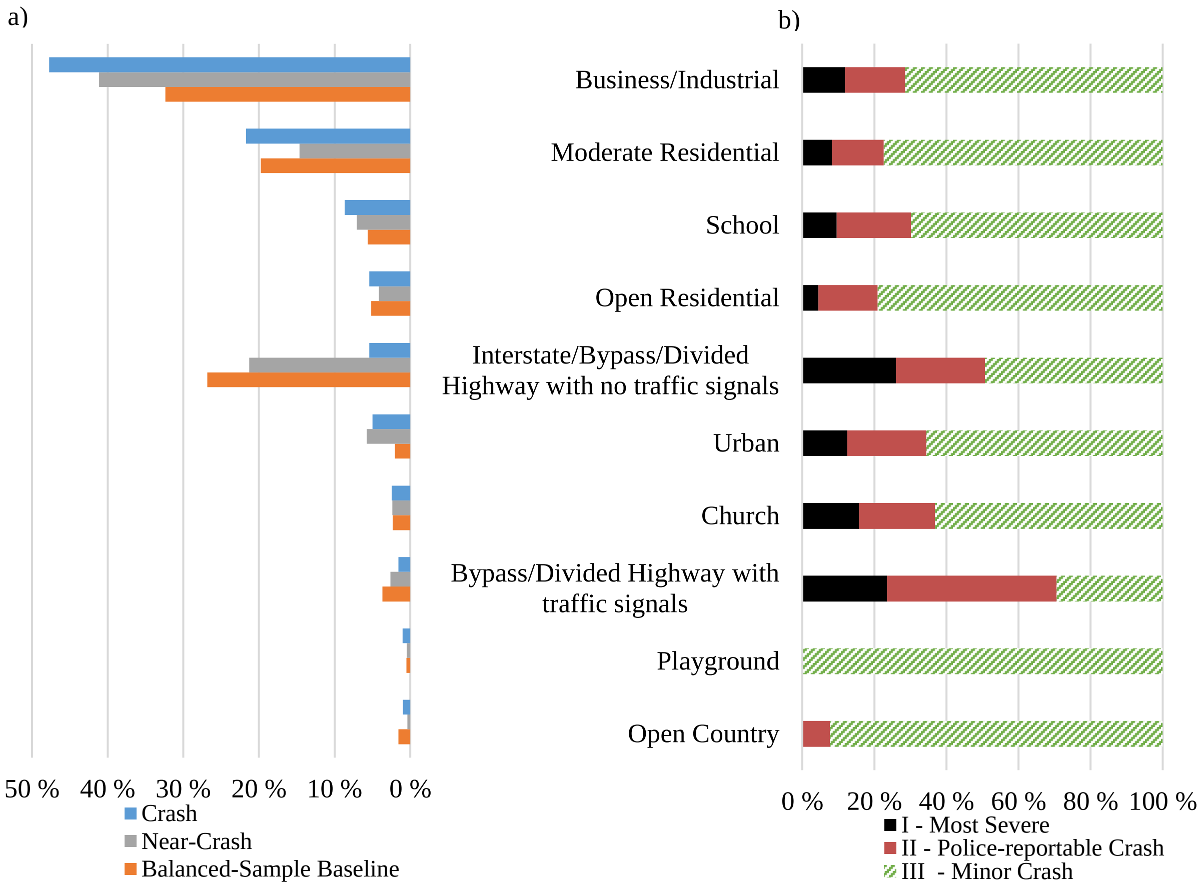

Figure 3. a) Relative proportion of crashes, near-crashes and baseline events depending on locality b) Relative proportion of crash severity depending on locality

In the next step, we concentrate on pre-incident maneuvers on interstates/bypasses/divided highways with no traffic signals. This variable describes the type of action or driving maneuver just prior or at the time of the event [Vtt16]. Within this category, 79 crashes (5.4 %), 577 near-crashes (21.3 %) and 5,367 (26.8 %) baseline events are included in our data set. Figure 4 depicts the relative proportion of pre-incident maneuvers within crashes, near-crashes and baseline events. 66 % of the time subjects went straight with constant speed. Fewer crashes (43 %) and near-crashes (42 %) occur within this type of scenario. Critical scenarios for human drivers are: going straight while accelerating, decelerating in traffic lane, changing lanes (intentionally and unintentionally), and merging. Therein, the relative proportion of crashes and near-crashes is higher than existing baseline events.

Furthermore, the pre-incident maneuver *decelerating in traffic lane* shows an interesting correlation: in this scenario more near-crashes (19 %) occur relatively compared to crashes (11 %). This may be explained by drivers avoiding an accident through an appropriate evasive maneuver.

Based on the available times series data, the initial velocity of each event is analyzed. Figure 5 shows the velocity distribution under the influence of different event types on interstates/bypasses/divided highways with no traffic signals. Within all baseline events, the velocity was below 60 km/h for 5.7 % of the time, below 100 km/h for 36.8 % of the time, and below 130 km/h for 97.9 % of the time. This analysis includes entering and exit ramps. Thus, if a L3+ system is able to handle all boundary conditions – e.g. unfavorable weather, toll gates, ramps – up to a velocity of 130 km/h, 97.9 % of baseline driving time may be covered. Between 50 to 110 km/h, more near-crashes and crashes occurred compared to the baseline events. This corresponds to the analysis of the pre-incident maneuver (Figure 4): a high proportion of crashes and near-crashes occurred while accelerating, decelerating or negotiating a curve.

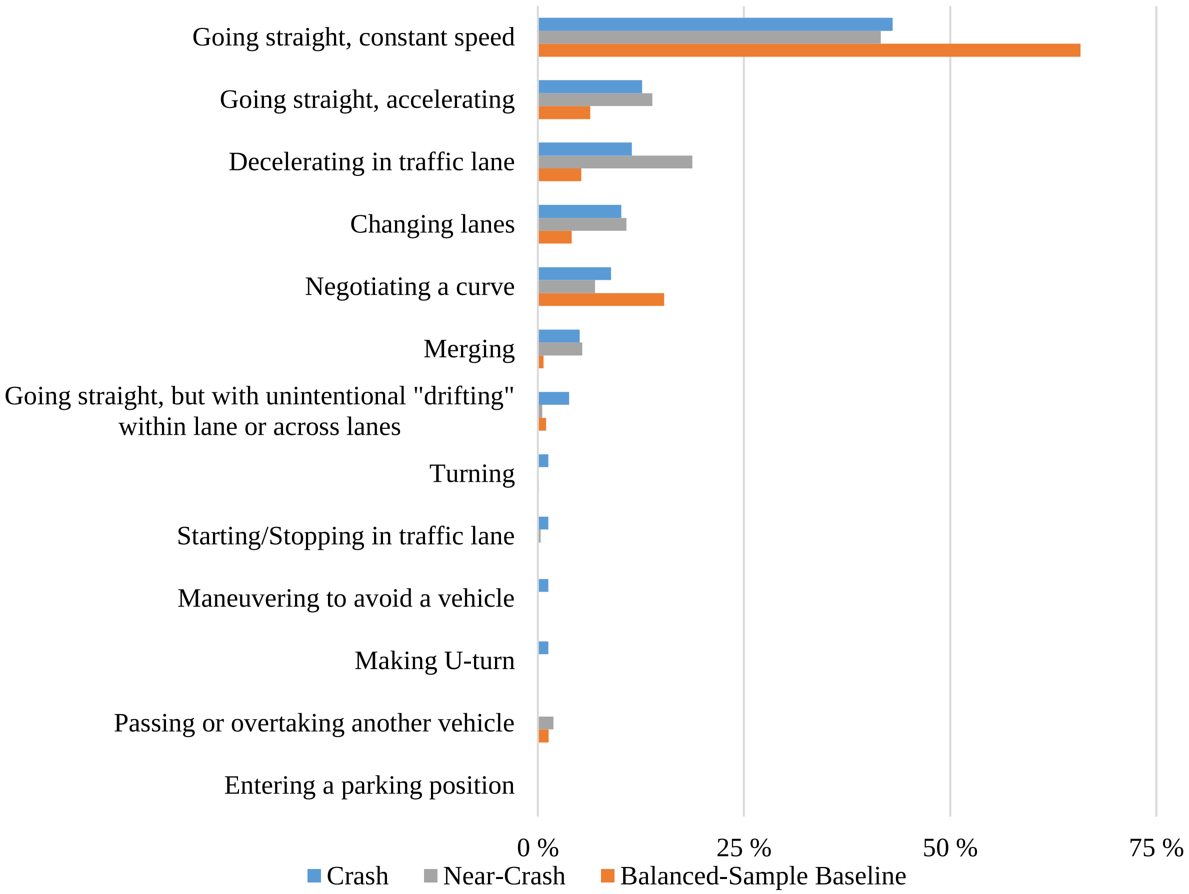

Figure 4. Relative proportion of pre-incident maneuvers for interstates/bypasses/divided highways with no traffic signals

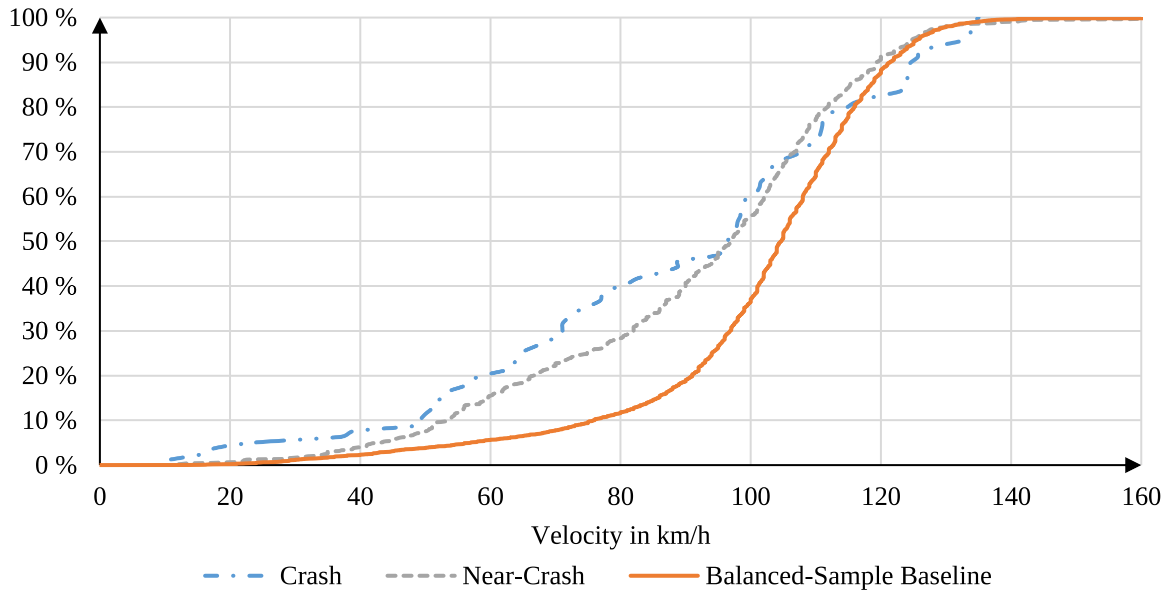

Figure 5. Velocity distribution for interstates/bypasses/divided highways with no traffic signals

Figure 6 shows the availability for different functionalities of a highway pilot and the influence of boundary conditions and technical requirements. Therefore, the baseline events are evaluated starting with a generic highway pilot (=100 %

- all trips within the SHRP2 NDS on interstates/bypasses/divided highways with no traffic signals may be covered by the highway pilot). Accordingly, all kinds of events and circumstances must be handled by a corresponding Level 3+ system, as a human driver cannot be expected to be promptly available as a fallback.

In the following steps, different boundary conditions and technical requirements are analyzed with respect to their influence on availability. Thus the cascade of boundary conditions/technical requirements and the influence on substituting manual driving by an automated system may be analyzed. If a system is not capable to handle situations with a watchman, officers or traffic controls such as toll gates 99.7 % of naturalistic driving time may still be covered. In addition, if the operational design domain is limited by unfavorable weather conditions, the availability is reduced from 99.7 % to 98.5 %. Boundary conditions/technical requirements such as automated driving on exit or entrance ramps, lane changes (detection of rear or side traffic) and construction zones (different/narrow drive paths) show higher influence on a customers' comfort advantage. If these scenarios cannot be managed by the automated system, the comfort advantage due to the automation is still 82.6 % of driving time. If the maximum speed is additionally limited to 130 km/h, the availability reduces to 80.8 %. A further speed reduction to 100 km/h results in a high decrease of availability (27.3 %). A maximum speed of 60 km/h and presence of a leading vehicle – here defined as traffic jam – results in an availability of 3.9 %.

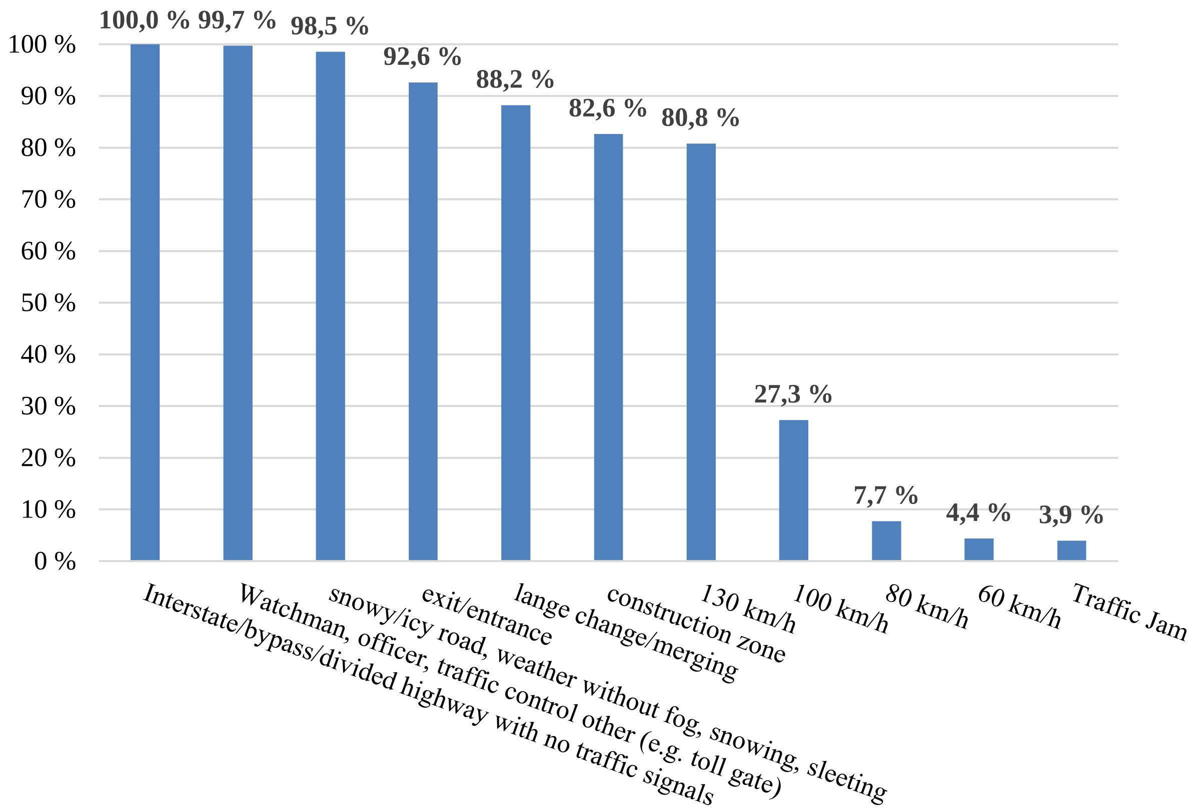

Figure 6. Top-down evaluation of availability for different functionalities of a highway pilot under the influence of boundary conditions and technical requirements

Beyond that, an automated driving function has a potential safety benefit due to avoiding or reducing criticality of (near-)crashes. On interstates/bypasses/divided highways with no traffic signals 79 crashes (5.4 %), 577 near-crashes (21.3 %) and 5,367 (26.8 %) baseline events occurred. For a generic highway pilot, it is assumed that these crashes and near-crashes can be avoided. The impact on safety and availability for different types of the operational design domain are analyzed in Figure 7. This analysis shows that boundary conditions such as weather, exit/entrance or construction zones have a high influence on the safety benefit of an automated driving function. The safety potential drops to 63 % of addressable crashes and 65 % of near-crashes if these cannot be addressed. Compared to the baseline events (83 % of availability) more critical events occurred under such conditions. Furthermore, low velocity automated driving functions (traffic jam, 60 and 80 km/h) have a higher safety potential compared to baseline events. A traffic jam highway pilot is able to address 9 % of crashes and 8 % of near-crashes while this function will only be offered in 3.9 % of baseline events. Thus, even a generic traffic jam feature has a higher impact on traffic safety compared to availability.

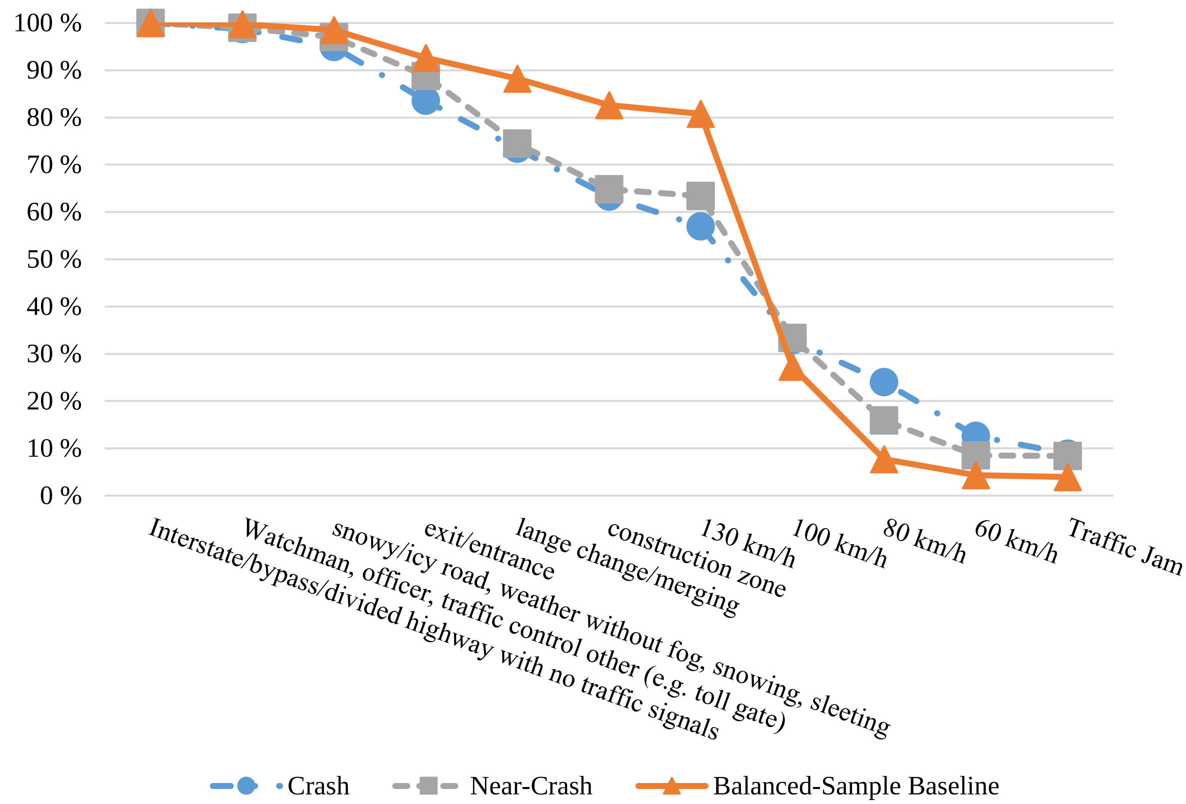

Figure 7. Top-down evaluation of safety potential for different functionalities of a highway pilot

To analyze the impact on collision avoidance, an investigation on GIDAS data has been conducted as well. In total 3,052 passenger vehicles on highways or similar (separated roadways without intersections and traffics lights) were included in our study. The set of all vehicles constitutes 100 % safety potential of a system for highways and comparable roadways. The top-down methodology of different boundary conditions and technical requirements were analyzed with respect to the influence on the safety potential as before. There was no relevant information in the database with respect to situations with a watchman, officer or traffic control such as toll gates. Consequently, there is no reduction in accident prevention potential. Without unfavorable weather conditions, the safety potential is reduced to 94 %. In the next step, vehicles driving on exit/entrance ramps, performing lane changes, merging maneuvers, or passing construction zones were excluded. Hence, the system benefit is reduced to 83 %. When the vehicle's speed prior to the situation becoming critical is below 130 km/h, the gain is 68 %. In traffic jams, with other vehicles present and a system's operating envelope of at most 60 km/h, the associated benefit is at about 9 %. All applied steps are displayed in Figure 8. In contrast to the NDS dataset, for GIDAS all vehicles on the respective type of road are analyzed. This leads to a vehicle-based focus.

DISCUSSION AND LIMITATIONS

The previous section has shown the potential safety benefit of automated driving functions. Additionally, the avoidance of accidents by human errors (e.g. impairment, inattention) during manual driving results in increased safety and comfort.

The high performance sensors installed for Level 3+ functionalities could additionally be used to improve active safety systems for manual or assisted driving. Within the NDS, comparable collisions also occurred on interstates/bypasses/divided highways with traffic signals. Thus, the operational field and performance of state-of-the-art active safety systems could be increased by harnessing these sensors.

By using the NDS's data, some limitations of our analysis need to be considered. On the one hand, only the time series data of the participants' vehicle is known. In contrast, in GIDAS the accident is reconstructed for everyone involved.

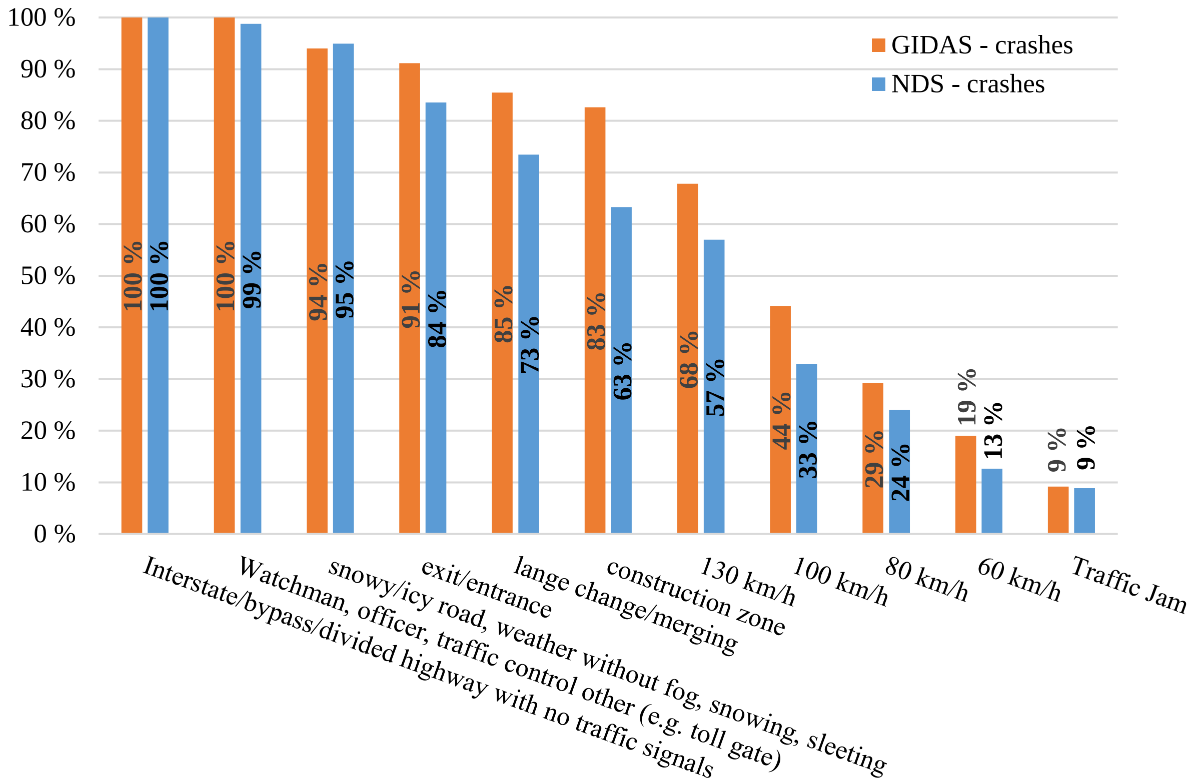

Figure 8. Top-down evaluation of safety potential for different functionalities of a highway pilot under the influence of boundary conditions and technical requirements

On the other hand, for some events specific time series data (e.g. velocity) was not included. In this analysis, events with missing data were excluded.
To investigate safety and comfort gain, it has been assumed that the automated driving function can consider crashes, near-crashes and baseline events. Furthermore, the NDS database is fairly limited with respect to crashes on interstates/bypasses/divided highways with no traffic signals (n=79).
Beyond that, misbehavior of other traffic participants has not been included in our analysis. An example could be a collision during a lane change that is caused by the speeding of the approaching vehicle.

CONCLUSION AND OUTLOOK

For automated driving systems, the balance of functionality, availability and safety is a crucial real-world deployment challenge. Consequently, this paper presents a prospective effectiveness assessment based on naturalistic driving data. For a top-down development process of Level 3 and beyond systems, an evaluation of technical requirements for upcoming automated driving functions is essential.

In this paper, a new method to assess and quantify this impact has been presented. The conducted analysis shows that a generic highway pilot can significantly improve driver comfort, since 26.8 % of the analyzed baseline events are highway driving. Especially the prevention of severe highway crashes leads to a high safety potential. Furthermore, a high proportion of near-crashes on the highway indicate a rather demanding driving task even for human drivers. An analysis of crashes in the GIDAS database shows comparable results and allows to create a range of safety benefits of highway pilots.

In conclusion, the conducted analysis enables a differentiation of various operational design domains on customers' comfort and reduced criticality due to avoided crashes or near-crashes.

ACKNOWLEDGMENT

The findings and conclusions of this paper are those of the authors and do not necessarily represent the views of the VTTI, SHRP 2, the Transportation Research Board, or the National Academies.

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DEVELOPMENT AND IMPLEMENTATION OF SAFETY EVALUATION SCENARIOS FOR AUTOMATED DRIVING VEHICLES ON TEST BED

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Paper Number 19-0061

ABSTRACT

Regulation for the testing and operation of automated driving vehicles on public roadways has been recently developed all over the world. For example, the licensing standards and the evaluation technology for automated driving vehicles have been proposed in California, Nevada and EU. Like M-city, the test bed has been developed worldwide to evaluate automated driving vehicles and K-city has been developed as the test bed in Korea. The K-city has a variety of facilities such as merge, ramp, tollgate, tunnel, intersection and so on according to five road conditions: motorway, suburban road, urban road, community road and valet parking zone. Therefore, it is necessary to have automated driving evaluation scenarios that would actually be implemented in K-city. For scenario implementation as vehicle tests, automated driving vehicles are needed. The safety evaluation scenarios and criteria for level 3 and level 4 automated driving vehicles were developed in consideration of the actual driving conditions, the real road driving data, and the existed automated driving evaluation methods (ISO, NHTHA, and so on). Then, the safety evaluation scenarios were determined by considering whether the test bed could be realized, repeatable, and safety performance could be well assessed. In order to evaluate automated driving on actual test bed, vehicles as well as evaluation scenarios are needed. First of all, it needs an automated driving vehicle that is evaluated. The evaluated vehicle is called as a subject vehicle. Besides the subject vehicle, vehicles that can help evaluation are also needed and are referred to as target vehicles. Target vehicles have the ability to driving autonomously in accordance with the scenario, maintaining safety performance with the surrounding vehicles, and recognizing subject vehicle to measure safety criteria. For example, the target vehicles are used to produce a variety of situations, such as cutting in front of the subject vehicle, decelerating in front of the subject vehicle, or driving on the main road when subject vehicle is on the merge road. In the study, a subject vehicle and four target vehicles have been developed and utilized. To verify the developed evaluation scenarios, vehicle tests were conducted using subject vehicle and target vehicles. The subject vehicle has level 3 and level 4 of automated driving that have diverse functions such as lane keeping and lane change. In accordance with the scenarios, all vehicles were self-driving and the subject vehicle was checked whether it meets the evaluation criteria. Through vehicle tests, the developed evaluation scenario was verified to be feasible on the test bed and to evaluate the performance of subject vehicle well. In this paper, the vehicle test result of merge scenario is presented among various motorway scenarios.

INTRODUCTION

Evaluation technology of the automated driving is actively developed in accordance with the rapid development of automated driving system around the world [1, 2]. In the case of the advanced driver assistance system (ADAS), which is the basic technology of automated driving system, standards and evaluation techniques have been developed by organizations such as ISO, NCAP, and NHTHA [3, 4, 5]. About automated driving, research and collaboration have been conducted to create standards and evaluation criteria worldwide, including the EU and the United Nations [6, 7].

Since the automated driving system must be evaluated while driving, the driving environment is very important. For the autonomous driving, a system such as a temporary driving license for automated driving system was institutionalized [8, 9]. Initially, it was started on Nevada and California in the United States of America, and now the temporary driving license is being institutionalized in several countries around the world, including Korea. The temporary driving license system can be helpful for developing autonomous driving technology because it can travel with various vehicles on actual roads. However, it is difficult to reproduce the desired and repeated situation. Therefore, there is a great need for a test bed as well as an actual road for autonomous driving technology. M-city in the United States was built as a test bed specialized in automated driving evaluation [10]. Following M-city, many test beds specially developed for automated driving are being developed around the world, and K-city have been developed in Korea [11]. K-city simulates several driving environments such as motorway, suburban roads, urban roads, community roads and valet parking zone. In addition, facilities that can have an influence on autonomous driving are prepared such as such as V2X infra, GPS block tunnel and sensor barricade.
In this study, automated driving evaluation scenarios and criteria that can be implemented by K-city have been developed. Since the automated driving is an integrated and developed system of the existing ADAS, the existing ADAS evaluation technology was applied to the development of the automated driving evaluation technology. In addition, various evaluation criteria were developed considering actual driving data and physical characteristics of vehicles. The evaluation criteria consist of the states of the ego vehicle and the interactive states of the surrounding vehicles. To represent the interactive states of the surrounding vehicles, a variety of indices already exist such as clearance, time gap (TG), time to collision (TTC) and so on [12]. In this study, the lane keeping safety distance and lane changing safety distance are devised newly. Although various driving environments exist in K-city, only motorway scenarios are developed in this study since motorway is the closest environment to fully automated driving being realized. In the scenario verification, an automated vehicle to be evaluated and surrounding vehicles to assist in evaluation are needed. The basic automated driving function is need to the surrounding vehicles, because the vehicles is driven in accordance with the actual scenario. Using these vehicles, the evaluation scenario has been implemented and verified in K-city. In this paper, the vehicle test result of merge scenario is presented among various motorway scenarios. 3

THE CURRENT STATUS OF SAFETY EVALUATION OF ADV

Safety Evaluation Scenario and Criteria of ADAS

The automated vehicles generally is an integrated system of individual ADAS element technologies which are ACC, AEB, and LKAS. In order to evaluate the performance of the autonomous vehicle system, it is examined the evaluation scenarios and criteria of existing element systems. The test procedures are based on ISO, NHTHA and NCAP which focus the evaluation of vehicle safety system

ACC The ACC performance evaluation specified by ISO consists of straight-lane recognition performance, preceding vehicle identification performance, and preceding vehicle identification performance on curve lane. In straight-lane recognition performance test, the maximum recognition distance within 2 seconds is evaluated. In the identification performance test of the preceding vehicle, it is evaluated whether each front vehicle existing in the in-lane and the side lane in the straight road is recognized and identified. This is a test for verifying whether the ego vehicle follows the preceding vehicle on in-lane, without misrecognizing the vehicles on other lane. In the identification performance test of the preceding vehicle on curve lane, it is evaluated whether the ego vehicle can perceive and identify the preceding vehicle on curve lane. In addition, when the preceding vehicle is decelerated from the curved road, the behavior of the ego vehicle is also evaluated [3].

AEB The AEB performance assessment as defined by Euro NCAP is divided into two cases: City and Inter-Urban. For the City scenario, the AEB performance evaluation for stop targets is addressed for ego vehicle velocities of 10 to 50km/h. For the Inter-Urban scenario, the AEB performance evaluation is conducted for stop, moving, and deceleration targets for the ego vehicle velocity range of 30 to 80km/h. ISO AEB performance evaluation is based on two test scenarios . One is the case where the velocity of the preceding vehicle is 0km/h, the initial velocity of the ego vehicle is 80km/h, and the initial distance between the preceding vehicle and the ego vehicle is 120m. Second, the velocity of the preceding vehicle is 30km/h, the initial velocity of the ego vehicle is 80km/h, and the initial distance between the preceding vehicle and the ego vehicle is 120m. The criteria to be evaluated in the test scenario are as follows. It is evaluated whether the ego vehicle provides one or more warnings before 1.4seconds of automatic emergency braking, provides two or more warnings before 0.8seconds, reduces velocity of more than 10 km/h at the point of impact, and operates no emergency braking before TTC 3seconds [4].

LKAS The ISO LKAS performance test evaluates the acceleration, the operated velocity range and so on. The test is conducted within the speed range of 72km/h to 108km/h in a curved section of 800 m radius. In the scenarios defined by NHTSA, progress is made at 72km/h. Performance test is performed from a lateral speed of more 0.6m/s to a maximum speed at which the lane departure prevention performance is maintained [5].

Safety Evaluation Scenario and Criteria of automated driving system

In accordance with the rapid development of automated driving, evaluation scenarios and criteria for the automated driving system are being actively developed around the world. In this paper, large projects in the EU and UN have dealt with.

Adaptive After 2014, the EU began developing the Adaptive Self Assessment Technology project. Adaptive takes account of the reflection on legal factors and human factors. In addition, evaluation scenarios are classified into proximity scenarios such as parking lots, urban scenarios, and highway road scenarios. In evaluation, framework and methodology are focused. Assessment is done from various perspectives like technical, user related and in-traffic assessments. Also, impact analysis have also been conducted. Lastly, deployment perspective for automated driving have been presented. The project lasted about three years [6].

WP29 WP 29 means the UNECE world forum for harmonization of vehicle regulations which is a unique worldwide regulatory forum within the institutional framework of the UNECE Inland Transport Committee. UN Regulations contain provisions related to safety and environmental aspects. They include performance-oriented test requirements, as well as administrative procedures. With the development of the automated driving system world widely, WP 29 focuses on automated driving systems. WP 29 contain globally harmonized performance-related requirements and test procedures. WP 29 also provide a predictable regulatory framework for the global automotive industry, consumers and their associations. Overall, the regulatory framework developed by the World Forum WP.29 allows the market introduction of innovative vehicle technologies, while continuously improving global vehicle safety. WP 29 have two principle operating groups. One is WP29 Informal Group to provide strategic direction for automated technology. This group focuses intelligent transport systems and automated driving (ITS/AD). Another is a group which have developed the UN regulation concerning vehicle steering systems to permit certain levels of autonomy. This group is called as GRRF and the GRRF Informal Working Group. WP 29 categories automated functions as six classification [7].

ENVIROMENTS OF ADV TEST BED

For test operation of automated driving vehicles, diverse methods has been recently developed all over the world. For example, the licensing standards for automated driving vehicles have been proposed in California, Nevada and EU. Although licensing has the advantage of driving on a real road, it is necessary to use a test bed because it is difficult to repeatedly test various situations. M-city is a test bed specialized in a typical automated driving system. Like M-city, the test bed has been developed worldwide to evaluate automated driving vehicles and K-city has been developed as the test bed in Korea. The Korea Automobile Safety Institute under the Ministry of Land, Infrastructure and Transport developed a test bed for safety evaluation of automated vehicles. The test bed is called as K-city and constructed various road environments in 360,000 square meter space. K-city can be divided into five major areas. There are urban roads, community roads, motorways, suburban roads, and valet parking facilities. K-city has implemented roads, transportation and communication environments similar to actual roads consisting of signal / non-signal intersections, rotary intersections, building facades, parking facilities and child protection areas for these five roads and facilities.

Motorway

Motorway environment reproduces the exclusive road traffic environment capable of high-speed movement. This environment is composed diverse constructions which are merge, split, main road, tollgate, guardrail and tunnel. In this environment, driving test is available with wide velocity range. Functions, lane keeping, lane change and safety control with surrounding vehicles, can be tested in motorway.

Suburban Road

Suburban road environment recreates rural roads with insufficient infrastructure. This environment consists of rotary, a tree-lined street.

Urban Road

Urban road environment reproduces the road traffic environment of the city. This environment is composed diverse constructions which are signalized intersection, a bus-only lane, a bus stop and a temporary building.

Community Road

Community road environment reproduces the road traffic environment centered on pedestrians. This environment is composed diverse constructions which are a school zone, sidewalk and bicycle road.

Valet Parking Zone

Valet parking environment reproduce the parking environment where autonomous valet parking is possible. This environment consists of various shape parking spaces. Parallel, horizontal and oblique parking spaces are constructed.

Figure1. K-City Test Bed for Automated Driving System.

CRITERIA OF PERFORMANCE EVALUATION OF AUTOMATED VEHICLES

In this chapter, criteria for evaluating automated vehicles are presented. The criteria are calculated by taking into account the safety standards used in the existing ADAS, the actual road data, and the physical behavior of the vehicle. It is important to basically evaluate the state of the ego vehicle and evaluate interactive state with surrounding vehicles. Indices of safety with surrounding vehicles are clearance, time gap (TG), time to collision (TTC) and so on. In this paper, safety distance is devised as representing safety performance. In this study, since only the motorway environment is focused on, the driving situation can be largely divided into lane keeping and lane change. Different safety distances are suggested depending on the two situations.

States of Automated Vehicle

The states of the ego vehicle must be evaluated to confirm the abnormal behavior of the vehicle. Considering the existing ADAS evaluation criteria, the following state of charge is evaluated. First, it is necessary to evaluate whether the velocity of ego vehicle exceed or not in desired velocity by the scenario. And of course,
In the lane-keeping scenario, It should be evaluated whether the ego vehicle are driving inside the lane. It is important to evaluate longitudinal and lateral accelerations, which are related to abnormal behavior and ride quality. The permitted range of accelerations depends on the scenario. For example, a large area longitudinal acceleration is allowed in an emergency scenario where a front vehicle cuts in abruptly. On the other hand, a small area longitudinal acceleration is allowed in a normal driving scenario. As another example, the allowable

lateral acceleration in the lane-keeping scenario and the lane-changing scenario is different. The criteria for the states are different according to each scenario. The criterian is decided based on the existing ADAS evaluation criteria and the human driving data. The values of the specific states are given in the scenario description below.

Safety Distance in Lane Keeping Situation

Based on WP29, the safety distance in the lane keeping situation means the distance that the autonomous vehicle must proceed the safety distance control when the front vehicle is within the safety distance. For example, if the front vehicle cuts in at a distance within the safety distance, the automated vehicle must perform the safety distance control to maintain the distance over the safety distance. Safety distances are discussed internationally as in Eq. (1). The velocity of automated vehicle is multiplied by Time Gap, which means that the higher the speed, the higher the safety distance is required. The issue of how to set the time gap internationally remains an issue. In this study, the safety distance equation is presented considering the physical braking distance and actual driver driving data.

$$C_{LK} = \tau_{LK} \times V_{AV} \qquad \textbf{(1)}$$

where, τ_{LK} is time gap in lane keeping safety distance and V_{AV} is velocity of automated vehicle.

The physical braking distance can be calculated by the following parameters in consideration of the characteristics of automated vehicles that are currently being developed globally.

$$d_{brake} = (t_{sys} - V_{AV} / 2a_{\max,AV}) \times V_{AV} \qquad \textbf{(2)}$$

where, τ_{LK} is system delay which sets 0.3 second and $a_{\max,AV}$ is maximum decelearion of automated vehicle which sets -9 m/s^2.

The actual driving data analyzed the distances when drivers were following the preceding vehicle in steady state [13]. The data were collected for 125 drivers of various age and sex. The following distance of this data is as follows.

$$c_{following} = c_0 + \tau_{following} \times V_x \qquad \textbf{(3)}$$

where, c_0 is the zero-speed clearance which sets 2m, $\tau_{following}$ is the linear coefficient, and V_x is the ego vehicle velocity.

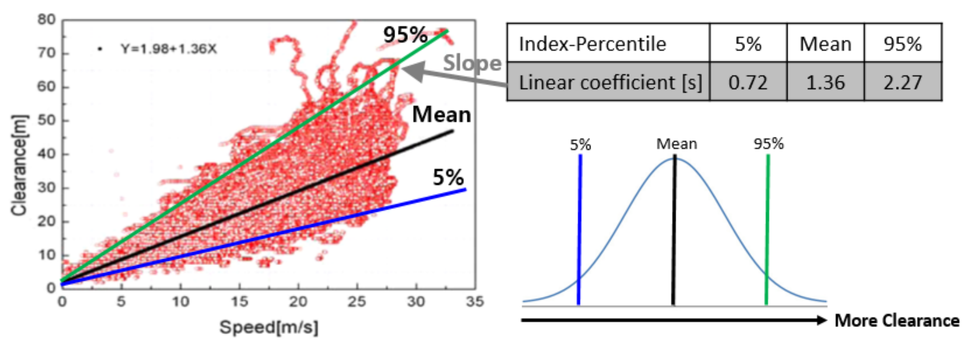


Figure2. Clearance driving data with a preceding vehicle in steady state following situation.

In pile-up accidents, the velocity of the preceding vehicle can become zero immediately without deceleration. Therefore, it need to be considered to calculate the safety distance over the braking distance in all velocity ranges. If setting the constant time gap to be discussed in WP29, time gap 2.3 second is needed to cover the braking distance of all velocity regions. This is too large in comparison with the actual driving data. And because too much safety distance is required in the low speed range, excessive and frequntely deceleration can occur. Therefore, the constant time gap is not proepr. If the time gap varies according to the velocity as Eq. (1), the safety distance is larger than the braking distance of all the velocity regions and does not largely differ from the driving data. Therefore, the safety distance in the lane keeping situation is proposed based on braking distance and driving data as Eq. (4).

$$C_{LK,proposed} = \tau_{LK,proposed}(V_{AV}) \times V_{AV} + c_0 \qquad \textbf{(4)}$$

$$\tau_{LK,proposed} = 0.8 + \left(\frac{1.6 \times V_{AV}}{36.1}\right) \qquad \textbf{(5)}$$

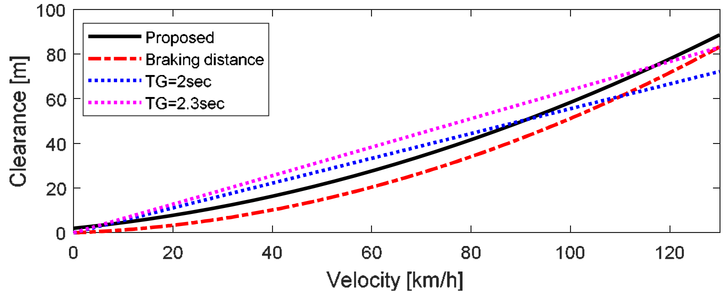


Figure3. Proposed safety distance in lane keeping.

Safety Distance in Lane Change Situation

Unlike lane keeping situation, which are important only for a preceding vehicle, all surrounding vehicles are important in lane change situation. Therefore, the lane change safety distance can be shown in Fig. 1. This distance indicates that a lane change is possible when no vehicle is present in this area. The vertical length of the area equals the lane width and the horizontal length consists of three distances which are a side, a rear and a front. The side distance is equal to the width of the ego vehicle.

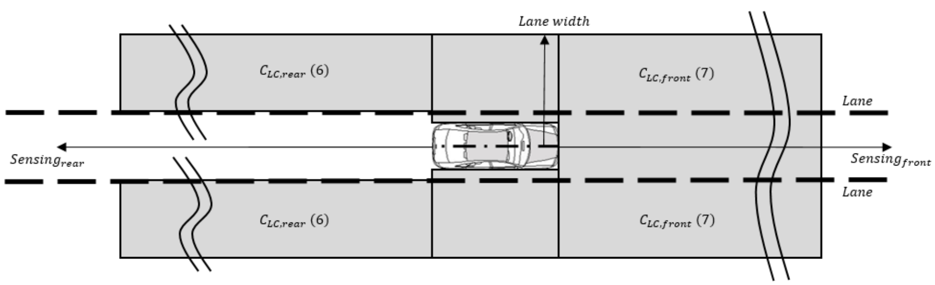


Figure4. Area by safety distance in lane change situation.

Eq. (6) indicates the rear distance which is calculated as a distance at which one second time gap is secured with a normal deceleration amount of the side-rear vehicle.

$$C_{LC,rear} = \begin{cases} (V_{rear} - V_{AV}) \times t_B + (V_{rear} - V_{AV})^2 / (2a_{rear}) + V_{rear} \times t_G & \text{If } V_{rear} \geq V_{AV} \\ V_{rear} \times t_G & else \end{cases} \qquad \textbf{(6)}$$

where, V_{rear} is the velocity of the rear vehicle on target lane, t_B is time delay to reach target deceleration which sets 0.3second, a_{rear} is normal deceleration of the rear vehicle which sets -3 m/s^2 and t_G is time remaining between vehicles after the approaching vehicle decelerates which sets 1second.

If a front distance is applied to a rear distance, the safety distance is too large. In this case, since lane change is possible only when the vehicle does not exist in an area that is too large, it is difficult to perform lane change in practice. Therefore, the front distance is calculated by changing the parameters in consideration that the vehicle to be decelerated is an ego vehicle. Eq. (7) indicates the front distance

$$C_{LC,front} = \begin{cases} V_{AV} \times t_G & \text{If } V_{front} \geq V_{AV} \\ (V_{AV} - V_{front}) \times t_B + (V_{AV} - V_{front})^2 / (2a_{AV}) + V_{AV} \times t_G & else \end{cases} \qquad \textbf{(7)}$$

where, V_{front} is the velocity of the front vehicle on target lane and a_{AV} is maximum decelearion of the ego vehicle which sets -9 m/s^2.

AUTOMATED DRIVING SYSTEM TEST SCENARIO

As described above, the K-city environment consists of motorway, suburban road, urban road, community road, and valet parking. In this paper, only motorway scenario is developed because the commercialization of fully autonomous driving is the closest in motorway. In the motorway, the driving function is largely divided into lane keeping and lane change, and scenarios are developed in consideration with situations that can occur according to each function. Table 1 shows test scenarios for the automated driving vehicle.

Table1.
Test scenarios for the automated driving vehicle.

Environment	Main Function	Specifics	Test No.
Motorway (+Suburban Road)	Lane Keeping	Solo Driving	M-1-1
		Preceding Vehicle	M-1-2
		Cut-in Vehicle	M-1-3
		Cut-out Vehicle	M-1-4
	Lane Change	Overtaking	M-2-1
		Merge	M-2-2
		Split	M-2-3

Motorway Lane Keeping Test (M-1)

Scenario the automated driving system should be able to keep the lane in solo driving (M-1-1). Lane keeping performance should be evaluated while varying the various velocity ranges and various curvatures within the road regulation. In addition, evaluation need to be conducted with surrounding vehicles in the vicinity. The automated driving system should be able to keep the lane as maintaining safety with a preceding vehicle (M-1-2). Along with lane keeping performance, it is necessary to evaluate whether the safety is maintained for various behaviors such as constant velocity, acceleration and deceleration of the preceding vehicle. The automated vehicle should be able to keep the lane as responding about sudden change of traffic condition such as cut-in case (M-1-3). It is necessary to evaluate the lane keeping and safety maintenance performance against the various behavior of the vehicle which performs cut-in maneuver from the adjacent lane to the in-lane. The automated vehicle should also keep the lane as responding about sudden change of traffic condition such as cut-out case (M-1-4). When a preceding vehicle is slower than the desired velocity of the automated vehicle, the automated vehicle need to follow the velocity of the preceding vehicle. It is necessary to assess whether the automated vehicle will recover the desired velocity when the preceding vehicle perform cut-out maneuver from the original lane to the adjacent lane.

Performance evaluation First, the lane keeping performance should be evaluated at various curvature and velocity conditions. And, when the surrounding vehicle exists, the maintenance of the safety with the surrounding vehicle must be evaluated. It should be assessed whether clearance with a preceding vehicle stay above a lane keeping safety distance. About the velocity, the desired velocity or the velocity of the preceding vehicle or the desired velocity recovery should be assessed depending on the scenario. Finally, in order to evaluate ride comfort and abnormal behavior, it is necessary to evaluate whether the longitudinal and lateral accelerations of the automated vehicle are maintained within a certain value.

Table2.
Performance evaluation of lane keeping situation.

Performance Index	Criteria
Lateral Position	Lane Keeping
Velocity	Desired Velocity / Velocity of Preceding vehicle
Longitudinal Acceleration (Normal Case)	$-3 \leq a_x \leq 2$

Longitudinal Acceleration (Severe Case)	-9 $\leq a_x \leq$ 2
Lateral Acceleration	-1 $\leq a_y \leq$ 1
Safety with a preceding vehicle	By lane keeping safety distance (4)

Motorway Lane Change Test (M-2)

Scenario Lane change can be classified as two cases. First, a case where a lane change is made by an influence of nearby vehicles on a normal road is referred to as a discretionary lane change (DLC). The most representative situation for DLC is overtaking situation (M-2-1). Therefore, when a preceding vehicle is slow or stopped, it should be evaluated whether the lane change is proceeding while maintaining the safety of the surrounding vehicles. Scenarios can be implemented by varying the velocity, the number and the location of the preceding vehicle and the side lane vehicles. Unlike DLC, a case where a lane change should be completed by road conditions is called a mandatory lane change (MLC). Representative situations of MLC are merge (M-2-2) and split (M-2-3). In order to perform DLC, the automated driving system should operate with the MAP. The automated vehicle must be to determine if it is located at merge or split. Then, the lane change need to be completed in limited distance and time constraints. In the merge scenario, various merge situations can be implemented by changing the position, the velocity and number of the vehicle in the target lane. In the split scenario, it is possible to implement various split situations by changing the preceding vehicle go to split lane or the preceding vehicle go straight in original lane.

Performance evaluation In a lane change scenario, the first thing to evaluate is the success of the lane change. In the case of an overtaking scenario, it is possible to perform a lane change while maintaining the safety of the surrounding vehicles, but it is also possible to maintain safety with a preceding vehicle by decelerating. In the case of merge or split scenario, the lane change must be successful while maintaining the safety of the surrounding vehicles. The lane keeping safety distance and the lane change safety distance are used for evaluation of safety with surrounding vehicles. Finally, it is necessary to evaluate whether the longitudinal and lateral accelerations of the subject vehicle are maintained within a certain area.

Table3.
Performance evaluation of lane keeping situation.

Performance Index	Criteria
Longitudinal Acceleration	-3 $\leq a_x \leq$ 2
Lateral Acceleration	-3 $\leq a_y \leq$ 3
Safety with surrounding vehicles	By lane change safety distance (6), (7)

IMPLEMENTATION OF EVALUATION SCENARIO UTILIZING AUTOMATED VEHICLES

In order to evaluate automated driving on actual test bed, vehicles as well as evaluation scenarios are needed. First of all, it needs an automated driving vehicle that is evaluated. The evaluated vehicle is called as a subject vehicle. Besides the subject vehicle, vehicles that can help evaluation are also needed and are referred to as target vehicles. Target vehicles have the ability to driving autonomously in accordance with the scenario, maintaining safety performance with the surrounding vehicles, and recognizing subject vehicle to measure safety criteria. For example, the target vehicles are used to produce a variety of situations, such as cutting in front of the subject vehicle, decelerating in front of the subject vehicle, or driving on the main road when subject vehicle is on the merge road. In the study, a subject vehicle and four target vehicles have been developed and utilized.

Subject vehicle

The subject vehicle must be capable of level 3 and 4 automated driving. The automated driving system is normally consist of localization, perception, motion planning and control functions. Localization function is achieved based on RTK GPS. In perception function, surrounding vehicles, obstacles and pedestrians are detected using six IBEO LiDARs. Lane also is detected by AVM camera and a front vision system. In motion planning function, proper motion is planned considering both a safety and a task. Safety means that automated vehicle can maintain safety with surrounding vehicles, obstacles and pedestrians. Diverse tasks, which are lane keeping, lane change and intersection driving, exist and the task is decided by the road environment. Control function determines the control input to track the planned motion. Model predictive control based automated driving algorithm is applied to merge situation, which is the vehicle test environment of this paper [14].

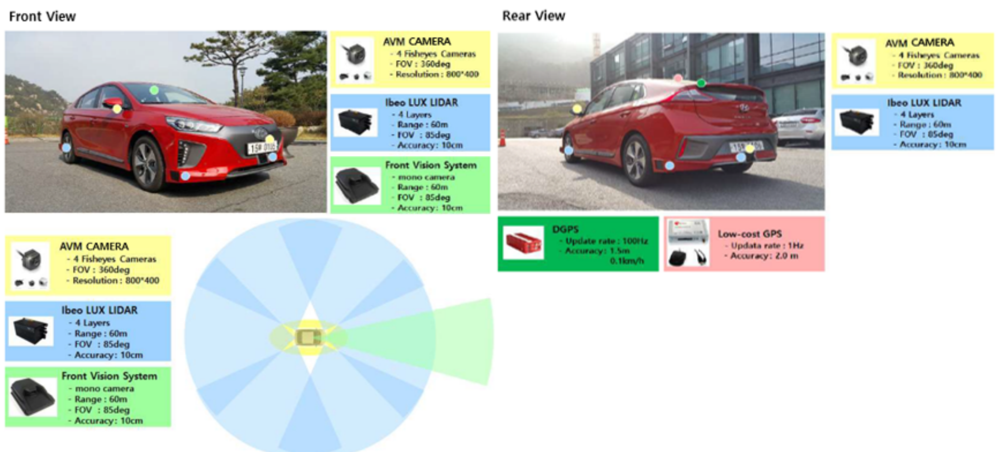


Figure5. Configuration and detection range of subject vehicle.

Target vehicle

Target vehicles have the ability to driving autonomously in accordance with the scenario, maintaining safety performance with the surrounding vehicles, and recognizing subject vehicle to measure safety criteria. Therefore, target vehicles also basic automated driving. As the subject vehicle, RTK GPS based localization function is equipped. LiDAR, Radar and Front Vision System based all-around vehicle detection can be possible to maintain safety performance with the surrounding vehicles, and to measure safety criteria of the subject vehicle. Target vehicle need to drive autonomously in accordance with a predefined scenario. For this purpose, target vehicle has a localization function using high performance RTK GPS. It also has path-generation algorithm which create a path as a predefined scenario. To decide desired steering torque as final lateral control input, path-tracking algorithm are implemented for tracking desired path [15]. Because target vehicle need to detect all-around vehicles for maintaining safety performance with the surrounding vehicles and measuring safety criteria of the subject vehicle, all-around vehicle detection module has been composed using LiDAR, radar and front vision system. For longitudinal control, two modules are considered. As first module, human driving data based ACC and AEB algorithms are equipped for safety control with surrounding vehicles [13]. As second module, scenario based velocity control algorithm is equipped. As final longitudinal control input, longitudinal acceleration is decided considering both modules. According to the above description, Fig. 6 represents algorithm structure of target vehicle. In addition, Fig. 7 shows configuration and sensor range of target vehicle.

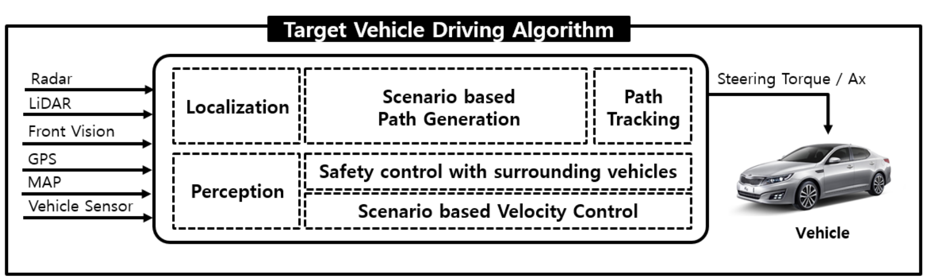


Figure6. Algorithm structure of target vehicle.

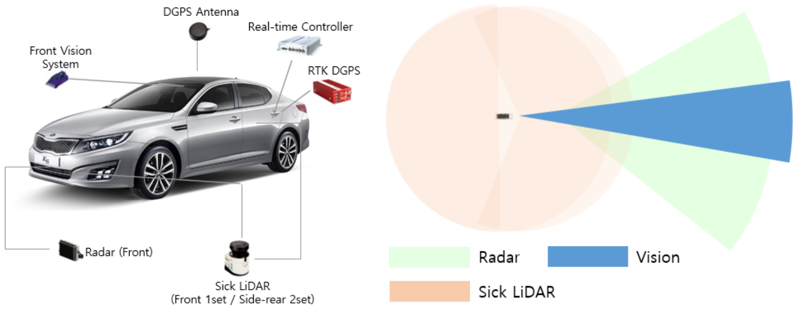


Figure7. Configuration and detection range of target vehicle.

VEHICLE TEST FOR VALIDATION OF EVAULATION SCENARIO

The actual vehicle test in K-city is carried out using the subject automated vehicle and the target vehicles which helps evaluation as mentioned earlier. Since all the scenarios cannot be shown, we present only merge scenario is presented. The merge situation is the most difficult scenario among motorway scenarios.

Test Case: Merge on Motorway

The merge scenario is shown in Fig. 8. The subject vehicle travels in merging lane, and the target vehicle which supports the evaluation travels on the target lane. Since the length of the merge lane is short as 100m in the K-city, vehicle test proceeds at a speed of 30km/h. In order to interfere with the merge of the subject vehicle, the target vehicle drives on side of the subject vehicle. Since the vehicle starts from a standstill, it must drive from the rear to meet the scenario situation. Fig. 9 represents the merge map and trajectory from the stationary state of two vehicles for the scenario situation.

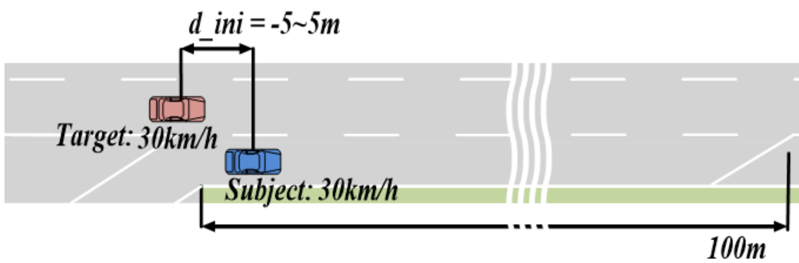


Figure8. Vehicle test condition in merge scenario.

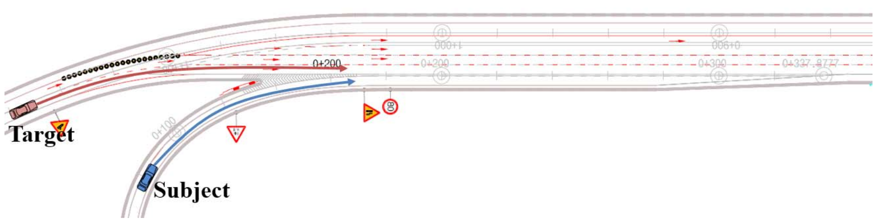
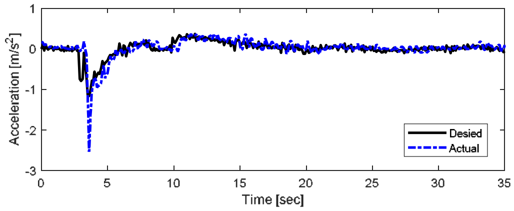
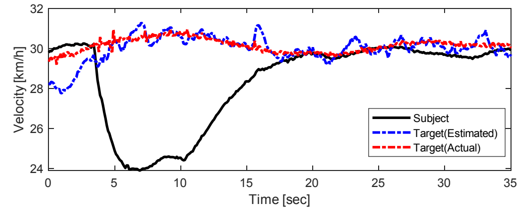


Figure9. Merge map and initial Trajectory for merge scenario condition.

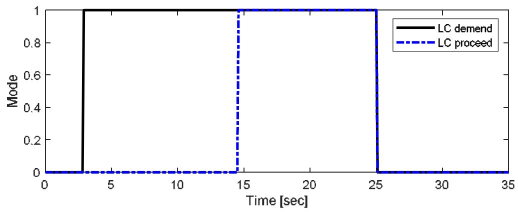
The results and sanpshots of the vehicle test are presented in Fig. 10 and 11 respectively. At 3sconds, the subject vehicle that has reached the start point of merge lane tries to make a lane change to the left, but the lane change is not possible because the target vehicle occupies on target lane. The subject vehicle judges whether to go ahead or rear of the target vehicle in consideration of the remaining distance of the merge lane and the state of the target vehicle. The subject vehicle decelerates since it decides that going rear of target vehicle is better. After the distance between the subject vehicle and the target vehicle is enough to perform lane change, the subject vehicle proceeds lane change to target lane at 14.9seconds. After the lane change is completed at 25seconds, the subject vehicle keeps a certain distance from the preceding vehicle in the lane keeping mode.



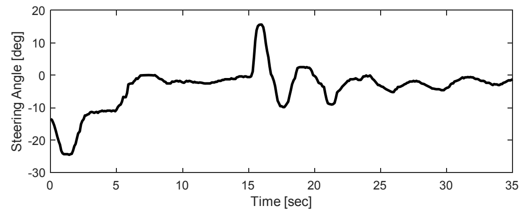
(a) Acceleration



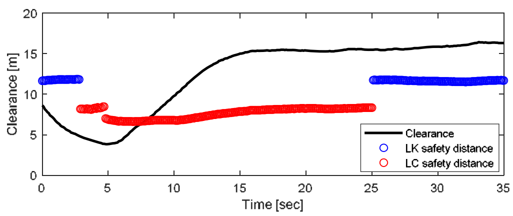
(b) Velocity of Each Vehicle



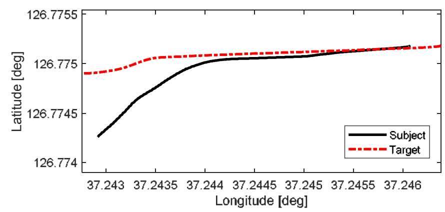
(c) Lane Change Mode



(d) Steering Angle



(e) Clearance



(f) Trajectory of Each Vehicle

Figure10. Vehicle test result of merge scenario.

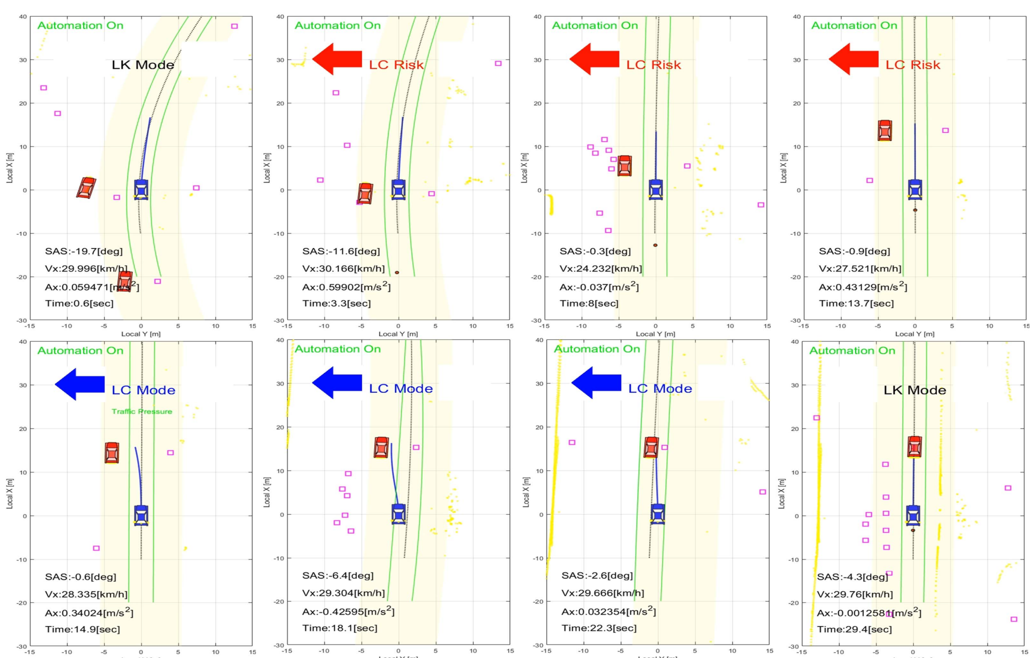


Figure11. Vehicle test snapshot of merge scenario.

CONCLUSIONS

According to the global demand for the development of evaluation technology of the automated driving system, the test bed has been developed worldwide to evaluate automated driving vehicles and K-city has been developed as the test bed in Korea. K-city simulates several driving environments such as motorway, suburban roads, urban roads, community roads and valet parking zone. In addition, facilities that can have an influence on autonomous driving are prepared such as such as V2X infra, GPS block tunnel and sensor barricade. In this study, automated driving evaluation scenarios and criteria that can be implemented by K-city have been developed. The evaluation criteria is developed considering existing ADAS evaluation criteria, driving data, and vehicle physics characteristics. The evaluation criteria consist of the states of the ego vehicle and the interactive states of the surrounding vehicles. To represent the interactive states of the surrounding vehicles, the lane keeping safety distance and lane changing safety distance are devised newly. The evaluation scenarios are developed taking into account repeatability, feasibility, and representative for driving situations. In the scenario verification, an automated vehicle to be evaluated and surrounding vehicles to assist in evaluation are needed. The basic automated driving function is need to the surrounding vehicles, because the vehicles is driven in accordance with the actual scenario. Using these vehicles, the evaluation scenario has been implemented and verified in K-city. In this paper, the vehicle test result of merge scenario is presented among various motorway scenarios. Future work requires development of evaluation scenarios and criteria for K-city remaining environments that are suburban road, urban road, community road and valet parking zone. In addition, verification would be conducted using one subject vehicle and four target vehicles.

* This research was supported by the Korea Ministry of Land, Infrastructure and Transport and the Korea Agency for Infrastructure Technology Advancement(Project No.: 18TLRP-B117133-03). This research was also supported by the Technology Innovation Program (10079730, Development and Evaluation of Automated Driving Systems for Motorway and City Road and driving environment) funded By the Ministry of Trade, Industry & Energy(MOTIE, Korea). This research was also supported by National Research Foundation of Korea(NRF) grant funded by the Ministry of Science, ICT & Future Planning (NRF-2016R1E1A1A01943543).

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DEVELOPMENT OF A SAFETY ASSURANCE PROCESS FOR AUTONOMOUS VEHICLES IN JAPAN

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Paper Number 19-0000

ASBTRACT

In order to introduce autonomous driving systems into the market, socially acceptable and technically sound safety assurance methodologies need to be agreed. In Japan, vehicle manufacturers and traffic safety experts have gathered regularly under the auspice of the Ministry of Economy, Trade and Industry, in a coordinated initiative to harmonize the required collaborative research, methodology development and standardization activities. Within this initiative, a comprehensive safety assurance process is to be agreed and made publicly available. The process shall be driven by top safety goals defined by authorities, shall consider the systems' performance limitations, and must be supported by state-of-the-art methodologies and real-world data. At this point, consensus on the overall safety assurance process for SAE Level 3+ autonomy in motorways as well as on the methodology to develop testing scenarios has been achieved and the results are hereby reported. The process and methodology are directly applicable to support the development of systems towards a safer autonomous driving society.

INTRODUCTION

Socially acceptable and technically feasible safety assurance methodologies and criteria need to be established as state-of-the-art global standards for a safe deployment of Autonomous Driving (AD) vehicles into the market. In order to guide this deployment in different regions, corresponding authorities such as the US National Highway Traffic Safety Administration, the UN Economic Commission for Europe, and the Ministry of Land Infrastructure, Transportation and Tourism of Japan have released their own safety guidelines [1, 2].

Product failures and design errors can be covered by an existing functional safety standard ISO26262:2011 [3]. This standard is used to evaluate if a process conforms and hence can be considered safe. In particular, the Safety of the Intended Functionality (SOTIF) process contained within the standardad provides coverage of SAE Level 2 AD systems. However, a specific safety assurance process for non-failure conditions that considers SAE Level 3 and higher (3+) AD systems and their performance limitations has not been established yet.

Traditional proving ground and field operation testing are insufficient to proof safety for vehicles with highly autonomous vehicles [4], and the incorporation of complementary virtual testing methodologies is essential. To support the development of these methodologies, joint efforts between industry and authorities are required.

In Japan, vehicle safety and AD experts have gathered regularly supported by the Ministry of Economy, Trade and Industry under the umbrella of the JAMA AD safety assurance working group, in a coordinated initiative to harmonize the required collaborative research, methodology development and standardization activities. A first scope for application of the developed methodologies has been set to SAE level 3+ AD systems on motorways [1].

Within this initiative and scope, our aim is to propose an AD system safety assurance engineering process for non-failure conditions that considers the system's performance limitations. A summary of the overall process is provided, followed by detailed description of the methodology to define virtual test scenarios and related criteria required to assure AD systems safety.

ENGINEERING FRAMEWORK FOR AD VEHICLE TEST SCENARIOS

A schematic of the overall safety assurance process developed is shown in Figure 1. The schematic is based on the project management V-model typically applied to develop connected vehicles, advanced driver assistance systems (ADAS) and AD systems [5]. The process covers all the product development stages from planning, design, implementation, evaluation (verification and validation), to release. Descriptions of each of these steps are provided below.

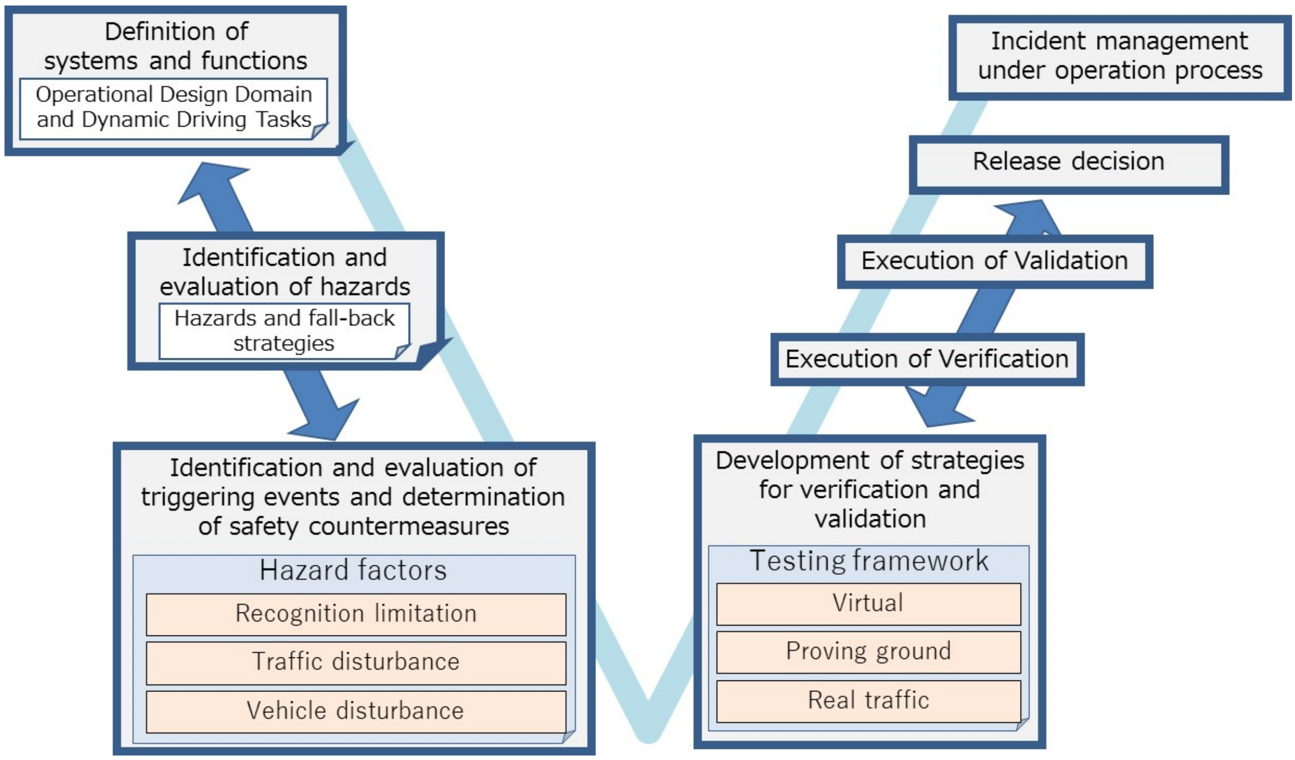


Figure 1 Overall scheme of the safety assurance process

Definition of systems and functions: Operational Design Domain and Dynamic Driving Tasks

The complete safety assurance process is to be conducted within well-defined and pre-determined operational and responsibility share boundaries. Therefore, upon the collection of existing information concerning the purpose and specification of different AD systems and functions, the Operational Design Domain (ODD), defined as the boundaries within the system is intented to operate, is described at the initial stage. ODD contents shall include at least information on roadway types, location within the road, vehicle speed ranges, and environmental conditions. The ODD definition needs to be structurized in a way that the user can understand and operate the AD system safely. On the other hand, the test scenarios that will be developed shall consider the ODD in a technically comprehensive way based on the physics of the system. For example, when rainy conditions are included in the ODD, the term 'rain' may be enough to communicate with the user, but the scenario might consider the effect of rain from different physical viewpoints such as the possible influence of raindrops on sensor performance, or the influence of rain on vehicle dynamics due to a decrease of the friction coefficient between the tires and the wet road surface. In order to organize all the ODD related information concerning the vehicle and its surroundings in a systematic manner, the Goal Structuring Notation methodology is applied [6]. This methodology is a standardized graphical argumentation technique widely applied to document and present safety goals and arguments in a clearer format than plain text [6].

The Dynamic Driving Tasks (DDT) and the responsibility share between the system and the driver are also defined at this point. It is noted that clarifying the responsibility share in accidents involving other vehicles that committed traffic rule violations or emergency rescue operations is particularly challenging, and solutions beyond vehicle development engineering may be required (e.g. crashes involving roads with potholes due to lack of road maintenance; crashes involving vehicles running in the wrong direction; or recognition limitations to take appropriate interventions in crashes involving emergency vehicles such as ambulances or police cars).

Identification and evaluation of hazards

Hazards, defined as potential sources of harm [2], are identified and evaluated at this point. Since hazards can be expressed at the vehicle behavior level, the ISO 26262 framework may be applied and the standardized hazard and risk assessment results may be diverted for the current purpose. If the hazards identified are judged unacceptable, a validation target shall then be specified for further analysis in the validation process. In addition, actuation strategies can be implemented at this stage to ensure safety for all traffic participants for the cases that fall within the ODD ranges but face hazards that the system is not designed to cope with (eg. when the system detects that the accuracy of a sensor measurement is lower than specified), or for cases that fall outside the ODD range (eg. when the vehicle enters a road type in which the system is not intended to work).

Triggering events and determination of safety countermeasures

Triggering events, defined as events that cause a risk to take place, are accounted for in this step. For hazards that have been judged unacceptable, the triggering events are analyzed under vehicle control categories, including traffic disturbance, recognition limitations, and vehicle disturbance sub-categories.

Traffic disturbance relates to traffic scenarios that may lead to a hazard as a combination of "road geometry", "ego-vehicle behaviour", and "surrounding vehicle location and motion". In order to handle a large amount of possible traffic disturbances, a well structured catalogue of foreseeable scenarios is jointly built by AD vehicle developers and traffic safety experts. The following sections in this paper ellaborate in detail on the construction of such catalogues.

Recognition limitations refer to conditions in which the sensor system fails to correctly recognize hazard factors. Examples include part mounting conditions (e.g. unsteadiness related to sensor mounting or manufacturing variability), environmental conditions (e.g. sensor cloudiness, dirt, light, etc), or vehicle conditions (e.g. vehicle inclination due to uneven loading that modifies sensor orientation, or vehicle state due to sensor shielding with external attachments such as bicycle racks).

Vehicle disturbance relates to situations in which, recognition and vehicle control command works correctly, but the vehicle fails to follow the control command. These may include vehicle conditions (e.g. total weight, weight distribution, mechanical functions) and driving environment including aspects that may affect vehicle dynamics (e.g. road surface irregularities and inclination, road friction, wind).

The safety countermeasures that will be applied and the systems and features that will intervene to avoid or mitigate the identified risk need to be decided for the triggering events that have been judged to require intervention. In addition, after confirming that the intervention is valid for the triggering event, the necessary functions may be either improved or newly developed according to the definition of systems and functions, and the system shall be updated accordingly.

Strategies for verification and validation

The strategies to validate and verify the system and to secure its safety are defined at this point. These strategies combine intensive virtual testing, with comparatively limited amount of physical tests in proving grounds and real-traffic environments.

The verification sub-process shall check the mathematical and physical correctness of the systems and functions developed and the safety countermeasures applied. It shall also confirm that all the safety specifications and requirements from the perspective of sufficiency of sensor-, algorithm- and actuator-related countermeasures are fulfilled.

The validation sub-process confirms that the systems and components including the safety countermeasures applied do not lead to an unreasonable risk for the traffic participants, and that the validation target previously defined is achieved, therefore demonstrating safety of the AD System.

Release decision

The release decision sub-process confirms that the safety of the AD system can be explained and that the remaining risk (if any) falls within an acceptable tolerance by reviewing whether adequate actions were implemented according to the results of the safety assurance process. Finally, based on the review results, it is decided whether the release of the system is acceptable or not.

Social contextualization of the engineering framework

The corresponding authorities in different regions are releasing safety guidelines. For example, the Japanese government recently released a technical safety guideline for AD systems, which reads 'Automated vehicle systems, under their Operational Design Domain (ODD), shall not cause any traffic accidents resulting in injury or death, that are rationally foreseeable and preventable' [1]. By contextualizing the AD systems safety assurance engineering framework proposed (Figure 1) with respect to governmental safety guidelines proposed by authorities, it is possible to develop engineering workframe that covers both social acceptance and technical aspects of the AD vehicles.

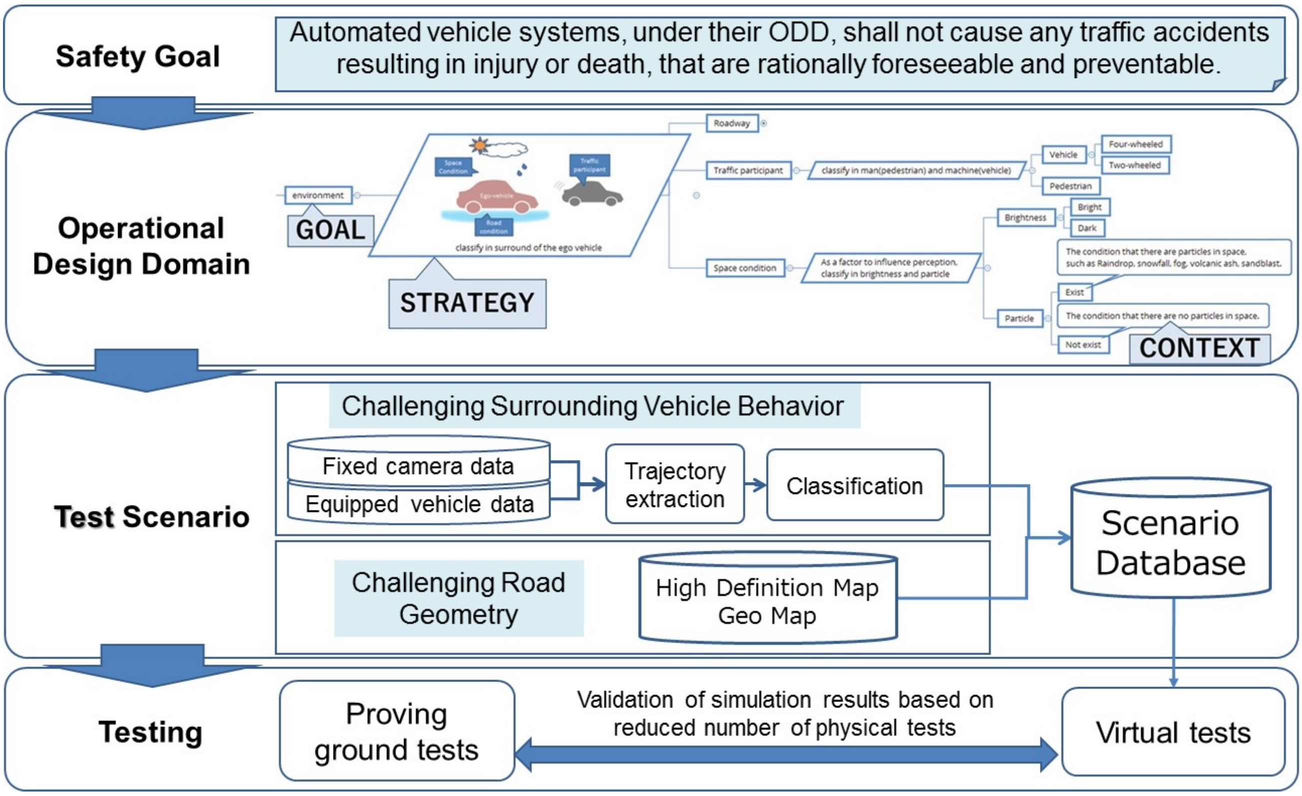


Figure 2 Top-down approach for social contextualization of the engineering framework for AD safety assurance

A scheme that illustrates such contextualization is shown in Figure 2. The scheme follows a top-down approach in which the ODD is defined considering the top safety goal, and test scenarios and validation strategies are developed under the same framework based on real-world data.

In order for AD test scenarios to be able to address the safety gudelines by the Japanese government, technical definitions for foreseeability and preventability becomes necessary. Foreseeable conditions are described as technically possible scenarios with quantitative parameter ranges. Preventable conditions are described as avoidable scenarios by means of technical intervention. The inter-relation between forseeability and preventability is illustrated in Figure 3. The focus of the scenario catalogue development in the current paper focuses on foreseeable and preventable scenarios according to the figure. It is noted at this point that preventing crashes in situations that involved other vehicles that committed traffic rule violations or extreme maneuvers is particularly challenging, and strategies complementary to vehicle engineering may be required (e.g. crashes involving vehicles running in the wrong direction at very high speeds).

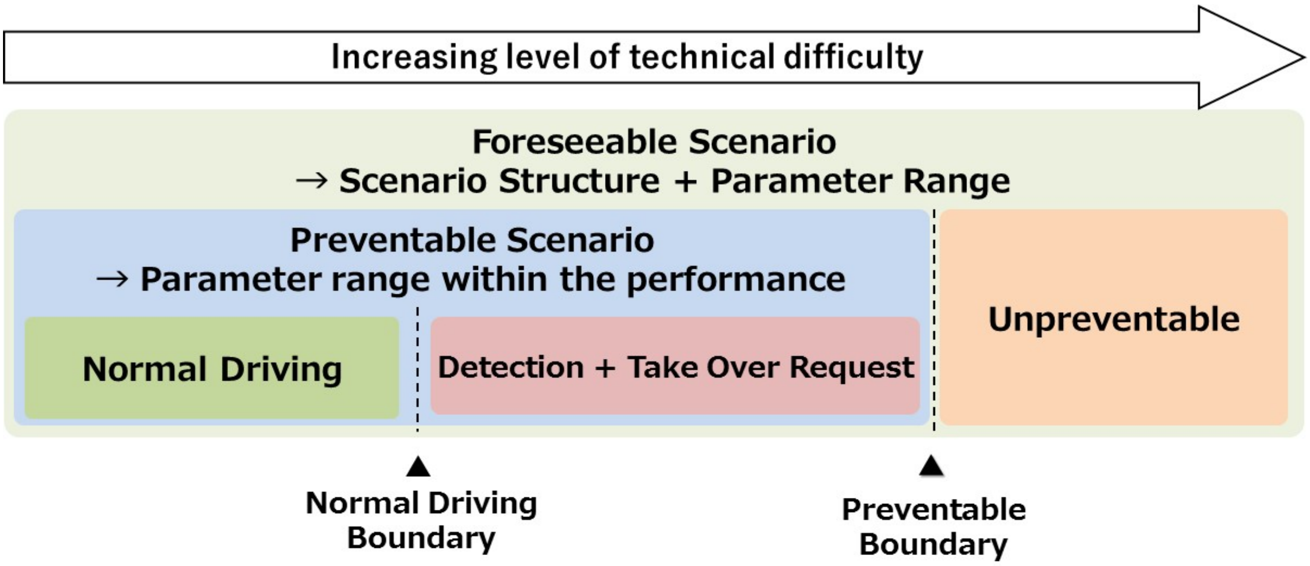


Figure 3. Forseeable and preventable scenarios and their inter-relations

Approach to AD safety test scenarios

Figure 4 summarizes the technical approach to develop test scenarios including quantified parameter ranges for AD vehicle safety assurance. First, scenarios are structured in order to cover holistic root causes from the point of view of the physics of the AD systems.

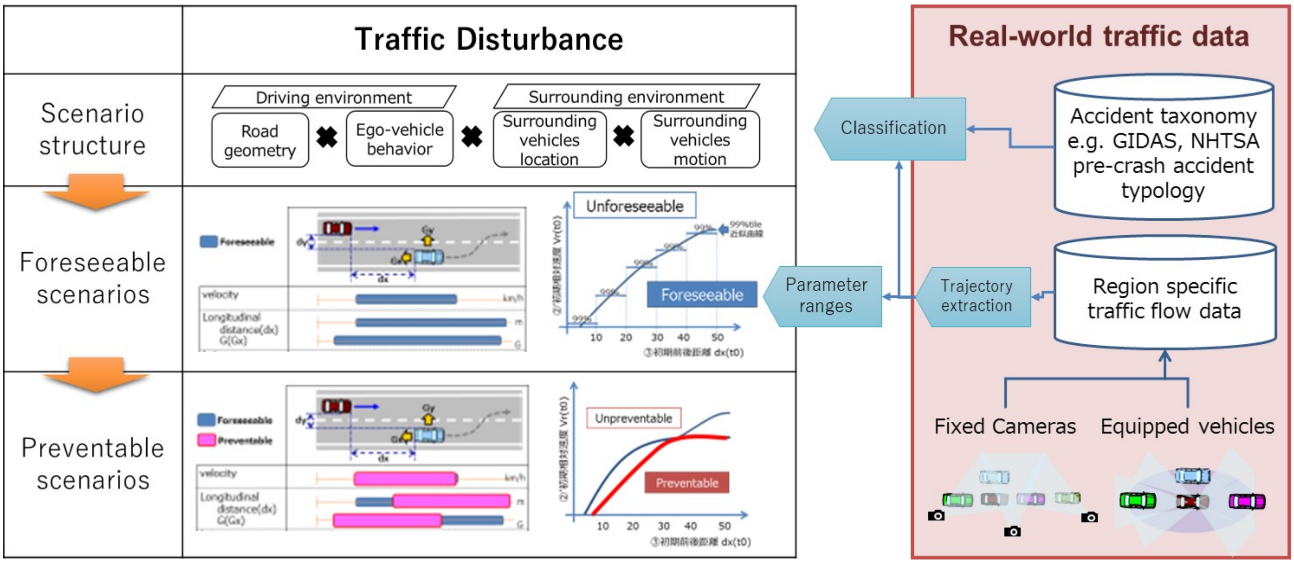


Figure 4 Approach to test scenarios for AD safety assurance

For each structured scenario, parameters and their ranges for foreseeable conditions are defined based on real-world traffic monitoring data. Among the foreseeable conditions, the ranges are narrowed down to those that correspond with preventable conditions. Both the evaluation of the completenesss of the structured scenarios as well as the steps to define ranges for foreseeable and preventable conditions are developed based on real-world traffic monitoring and accident data. The completeness of the structured scenarios is conducted based on accident data that contains information on pre-crash conditions. Traffic monitoring data is utilized to define the parameter ranges representative of foreseeable scenarios. Detailed descriptions of the methodologies to structurize and to generate test scenarios for AD safety assurance purposes follow.

STRUCTURE OF AD VEHICLE TEST SCENARIOS FOR SAFETY ASSURANCE

This chapter provides a description and practical guidance on the development of test scenario structure for AD safety assurance purposes. The scenario structure aims to cover all foreseeable root causes of traffic accidents that may possibly caused by AD vehicles. The applicability of the methodology proposed is limited, at this moment, to motorways.

Traffic scenario structure systematization

A scheme of the traffic scenario structure developed is presented in Figure 5. By analyzing and classifying traffic disturbances systematically and considering the driving environment and the surrounding environment, lists of traffic scenarios can be developed. Driving environment comprises Road geometry and Ego-vehicle behavior. Surrounding environment comprises surrounding vehicles location, and surrounding vehicles motion.

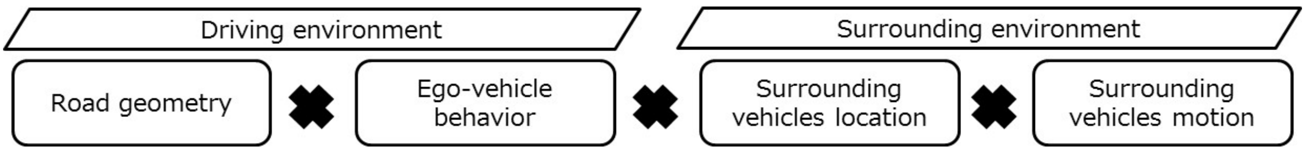


Figure 5. Structure for traffic scenarios

Road geometry classification and parameterization: Basic road geometry structure is defined according to the Japanese road structure ordinance [7], which provides technical standards for the development of roads in the country. In addition to road geometry related information such as cross sections, horizontal sections, sight distances, or speed changes, the ordinance includes parameters to ensure traffic safety and traffic flow smoothness.

Using the ordinance as a basis, road geometry sectors are categorized into Main road, Merging lane, Departure lane, and Ramp (Figure 6). Following this basic scheme, the corresponding critical road parameters for each of these components and for each scenario are defined based on expertise. As a result, critical parameters for traffic disturbances including the number of lanes, lane width, speed change lane and vertical gradients are proposed. Although the ordinance is generic, minor adaptations of the road structure may be required to become applicable to regions outside Japan.

Ego-vehicle behavior classification and parameterization: A lane change maneuver from a contiguous line or from a merging lane may differ in road geometry category, but share the ego-vehicle behavior. The same holds for lane keeping. Therefore, possible ego-vehicle behaviors are categorized in Lane Keep and Lane Change categories. This simple categorization of vehicle behaviours, in combination with the road geometry information provided previously, lead to a number of combinations (Figure 6).

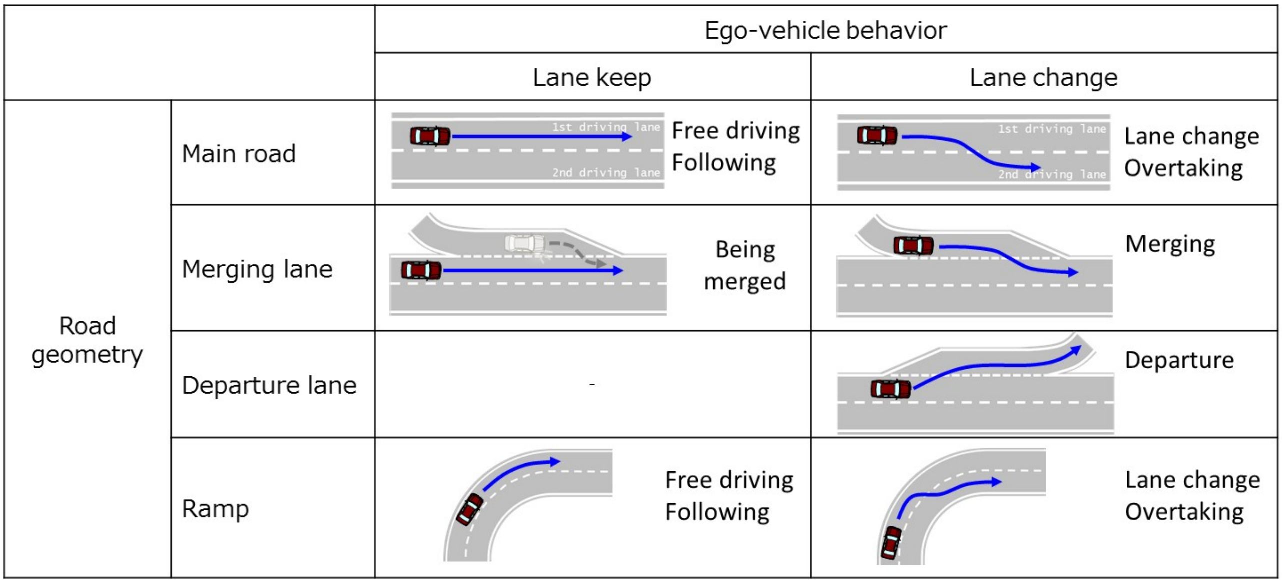
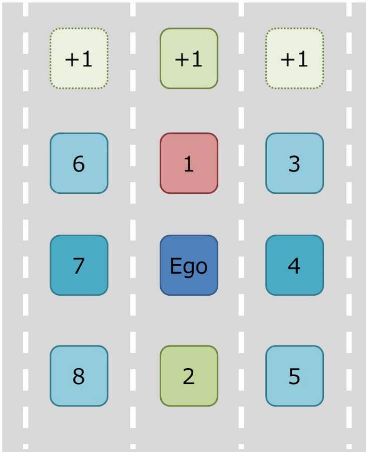


Figure 6. Road geometry and ego-vehicle behaviour parameters

Surrounding vehicle location classification and parameterization: The location of surrounding vehicles to be considered in the safety evaluation is defined according to adjacent locations in eight directions around the ego-vehicle, as these may invade the ego-vehicle's trajectory. In addition, when there is a large speed difference between the leading vehicle and the vehicle ahead of the leading vehicle, the former may cut out to avoid a collision. If this cut out occurs suddenly, the oncoming ego-vehicle may also need to intervene for crash avoidance. To account for this possible scenarios, the location of the vehicles ahead of the leading vehicle is also considered and is noted as '+1' (Figure 7, left).

Surrounding vehicle motion classification and parameterization: Possible motion of the surrounding vehicles is categorized in five groups: cut-in, cut-out, acceleration, deceleration, and synchronization. From the perspective of safety evaluation, it is possible to minimize the number of evaluation tests by focusing on the motion of the target participants that may obstruct the ego-vehicle's behavior (Figure 7, right chart).



Surrounding vehicle location	Surrounding vehicle motion: Cut in	Cut out	Accel.	Decel.	Sync
1.Lead		○		○	
2.Follow			○		
3.Parallel	○			○	
4. Parallel	○				○
EGO vehicle					
5. Parallel	○		○		
6. Parallel	○			○	
7. Parallel	○				○
8. Parallel	○		○		

'O' indicates a combination of surrounding vehicle location and motion that may become obstructive to the ego-vehicle

Figure 7. Surrounding vehicles locations (left) and cases that may become obstructive to the ego-vehicle (right)

Resulting structure for Autonomous Driving vehicle scenario

As a result of the systematization process described, a methodology to structure scenarios as a combination of road geometry, ego-vehicle behavior, and surrounding vehicles location and motion is proposed. Following this structure, a matrix containing 32 test scenarios was developed based on expert discussions (Figure 8). The completeness of this matrix may be evaluated based on comparative accident taxonomy. The critical parameters and ranges for each of the scenarios can be defined and quantified based on traffic monitoring data.

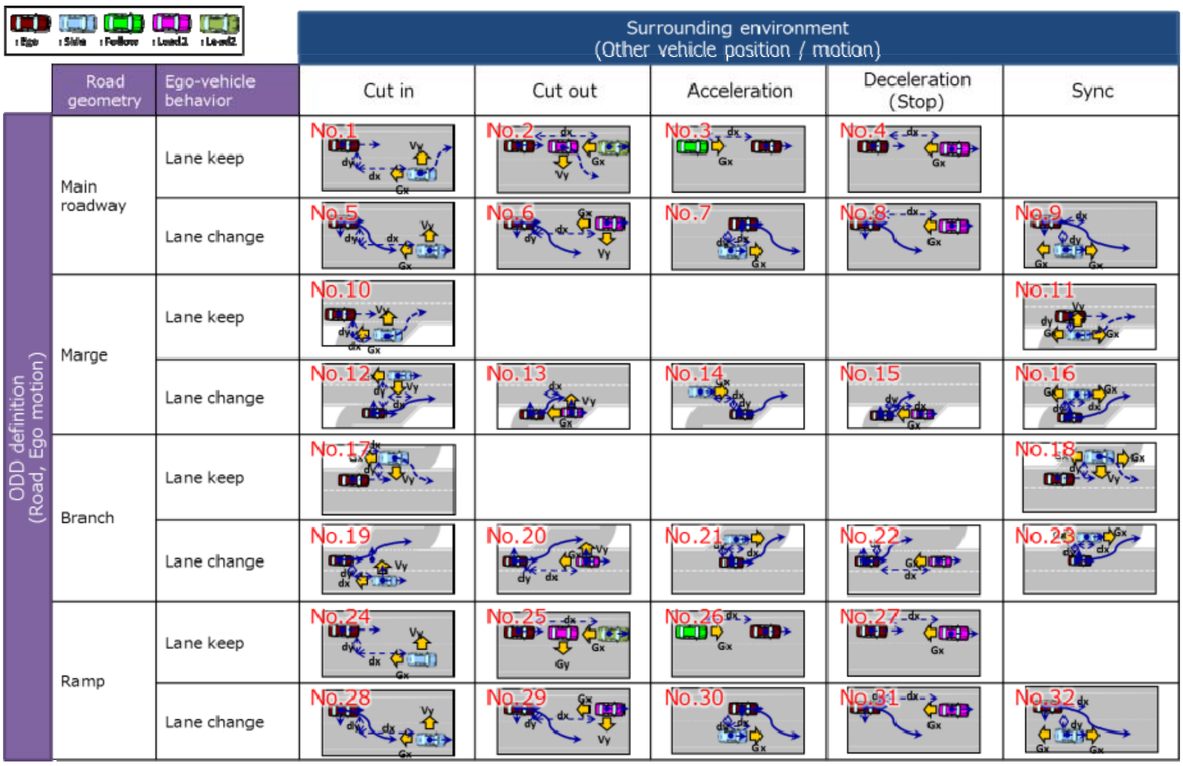


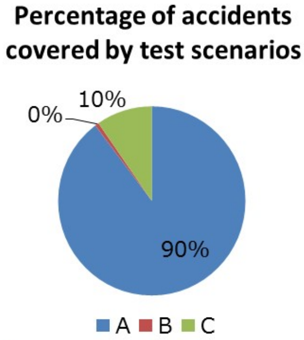
Figure 8. Traffic scenario matrix and corresponding parameters

Scenario matrix completeness evaluation based on accident data

The completeness of the scenario matrix proposed (Figure 8) may be evaluated by comparing its ability to cover accidents as reported in, for example, German in-depth accident study (GIDAS) database [8]. The underlying assumption of such comparison is that the accidents contained and classified in GIDAS represent all foreseeable scenarios in the German traffic environment.

GIDAS classifies traffic accidents according to predefined codes related to crash characteristics. Through a comparative taxonomy analysis between the GIDAS codes and the matrix of scenarios proposed (Figure 8), a relationship is established.

Classification		No. of codes		Total	No. of accidents
	Description	UTYPA	UTYPB		
A	Contained in scenario catalog	26	7	33	6,787
B	Available with variations according to road shape parameters	8	0	8	49
C	Not included in scenario catalog	24	13	37	731
				78	7,567



	Contents	No. of codes
B.1	There is a median strip	3
B.2	Reduced width	3
B.3	Special road merge section	2

	Contents	No. of codes
C.1	Reverse car	15
C.2	Stopped vehicle on road shoulder	8
C.3	Stopped vehicle on start of shoulder	5
C.4	Obstacle	3
C.5	Animal on road	2
C.6	Other	2

Figure 9. Scenario matrix evaluation based on GIDAS accident taxonomy

The upper left table in Figure 9 shows GIDAS accident code counts categorized based on the comparative taxonomy analysis. Categories A, B and C represent together 78 codes and 7,567 accidents in motoroways contained in the dataset analyzed. From these accidents, the comparative analysis shows that 33 codes and 6,787 accidents can be analyzed under the proposed matrix of scenarios (Figure 8), suggesting that the proposed matrix may potentially address nearly 90% of the motorway accidents reported in German motorways.

Category B comprises a total of 8 codes and 49 accidents (0.006% of all motorway accidents) that are related with road characteristics not covered by the matrix of scenarios. It is noted that the road geometry data applied to develop the list of scenarios was based on the Japan road structure ordinance [7], which may not cover some characteristics of German motorways. In order to provide coverage of the 8 remaining codes, adaptations of the proposed methodology to the German road characteristics may be required.

Category C comprises 37 codes and 731 accidents (10% of the total) that are not covered by the safety methodology proposed. Further analysis of the codes reveals that three code sub-categories (adding up to 28 codes) involved illegal maneuvers such as reversing in the motorway or illegal parking on the motorway shoulder (C1 to C3). The remaining 7 codes include obstacles or animals on the road and other unknowns (C4 to C6). The preventability of the crashes in this category (C) remains challenging for AD engineering intervention and call for complementary approaches that also involve, for example, rule enforcement.

GENERATION AND FORMATION OF AD VEHICLE TEST SCENARIOS FOR SAFETY ASSURANCE

This chapter provides a description and practical guidance on the process to generate test scenarios for AD vehicle safety evaluation by means of application of real-traffic data. The tests scenario structure is based on the previously proposed and the focus is on defining foreseeable scenarios including quantitative critical parameter ranges.

Road geometry parameter settings based real-world map data

To determine road geometry parameters, baseline road geometry critical parameters were assigned the most demanding values based on the Japan road structure ordinance, according to

Table 1.

Table 1. Baseline road geometry parameters from the road structure ordinance of Japan

Road parameters				Demanding value	
Cross section	Number of lanes			3	
	Width (m)			3.25	
	Center zone	Median (m)		1.25	
		Shoulder (m)		0.25	
	Side strip (m)			1.25	
	Linear gradient (%)			2.5	
Linear	Velocity (km/h)			120	100
	Horizontal alignment	Curve section	Radius (m)	570	380
			Transition section (m)	100	85
			Superelevation (%)	10	
		Speed change lane	Type	Direct	Parallel
			Direction	Deceleration	Acceleration
			Taper length (m)	70	60
			Pre-determined length (m)	110	220
	Vertical Alignment	Vertical Curve	Radius curve convex (m)	11000	6500
			Radius curve concave (m)	4000	3000
			Length (m)	100	85
		Vertical gradient (%)		5	6
Sight distance	Velocity (km/h)			120	100
	Sight distance (m)			210	160

In practice, real road geometries may not strictly comply with the road structure ordinance due to different reasons (e.g. merging lane length may be shorter than stipulated by the road ordinance due to limited construction space in crowded cities). Therefore, the previously defined baseline values for road geometry parameters need to be updated to reflect the actual strict road geometry conditions. With this purpose, dynamic map data are incorporated into the process. For example, a search of motorway characteristics in the region of Tokyo for “legal speed limit of 100 km/h” and “minimum curve section radius lower than 100 m” (Figure 10, left) shows numerous locations (resulting blue spots on the right of Figure 10). This exemplary search indicates that the baseline parameter values for road geometry (

Table 1) need to be updated from 380 m to no more than 100 m, to better reflect the actual road demanding parameter for curve radius in the region of Tokyo.

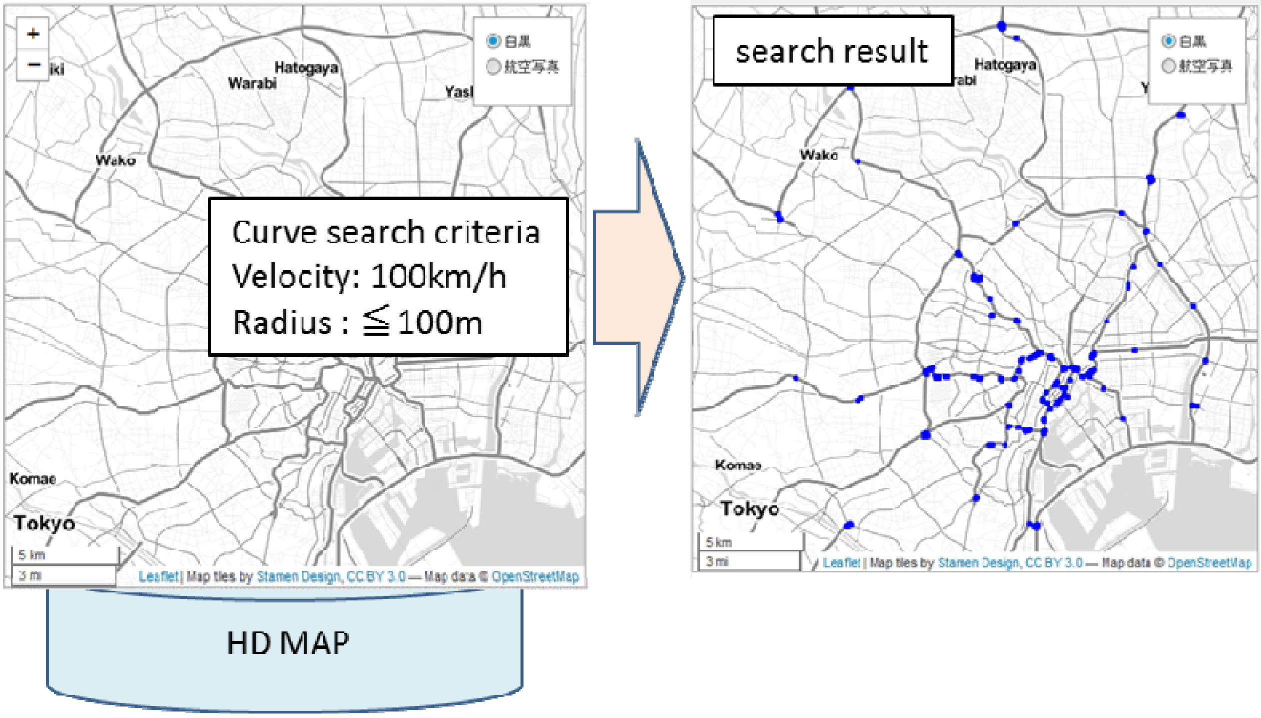


Figure 10. Data extraction utilizing dynamic map data

Surrounding vehicle foreseeable parameter ranges based on real-world traffic data

The process to derive critical parameter ranges in a cut-in test scenario (No.1 in Figure 8) is described in Figure 11. The basic idea is to define a list of surrounding vehicle motion critical parameters, and a simplistic model of the evolution of these parameters in time. In parallel, collection of real traffic data with stationary cameras and vehicles equipped with data collection devices is conducted, and correlation analysis between the simple surrounding vehicle behavior model and the corresponding field data measurements is conducted. Thereafter, parametric simulation studies are conducted to develop statistical distributions of a wide range of possible combinations of parameters. Based on these distributions, the parameter ranges that correspond with foreseeable scenarios are defined.

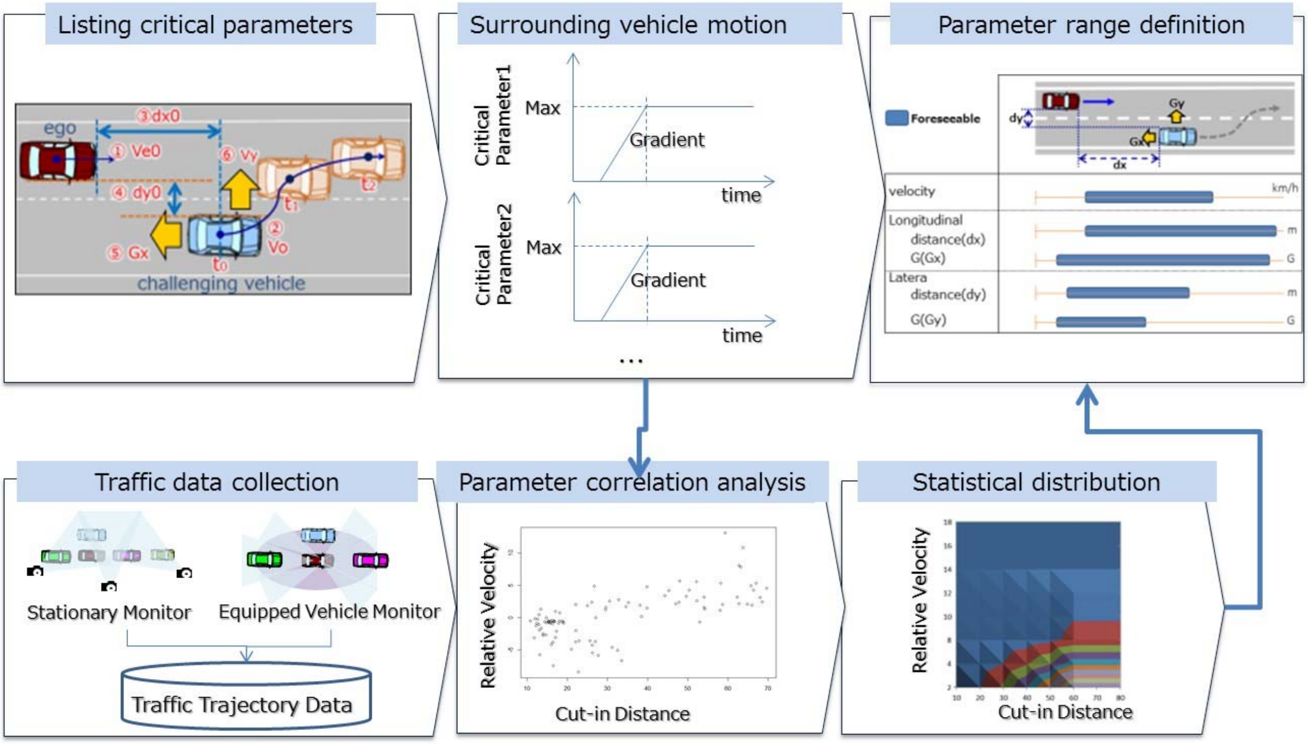


Figure 11. Process to extract surrounding vehicles motion to determine foreseeable scenario parameter ranges

Critical parameters and ranges: The same cut-in scenario is used to further ellaborate on the process to define critical parameter ranges. Similar processes are applied to extract the critical parameters for other scenario.

Two main aspects regarding the process to define critical parameter ranges are considered. The first one concerns the definition of the start and end time for the test scenario based on trajectory data (Figure 12, left). In this example, the start time of the scenario is defined by first identifying the lateral velocity of the challenging vehicle (Vy) at the timing (t1) in which the relative lateral distance between both vehicles (dy) becomes zero, and then by tracking back the lateral velocity (Vy) until the point in which it becomes zero. The end time is defined as the time in which the difference between the longitudinal velocities of the challenging and the ego-vehicle (Vo-Ve) becomes zero.

The second aspect regarding the process concerns to the definition of critical parameter ranges from the recorded trajectories. These ranges are defined by extracting cumulative ratios for large amounts of data cases (Figure 12, right). In the example, the cumulative ratio of lateral velocity (Vy) is obtained for different initial longitudinal distances (dx).

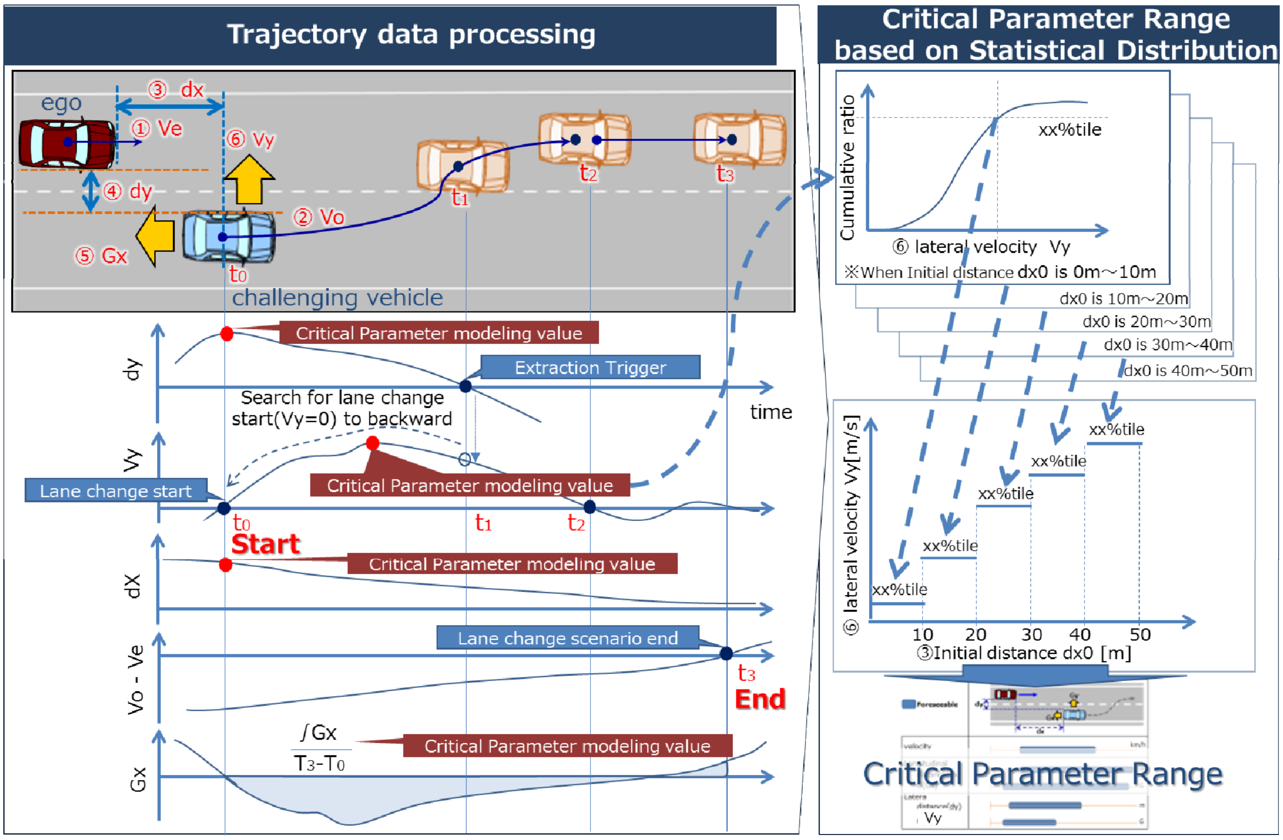


Figure 12. Definition of scenario start and end based on trajectory data processing (left) and critical paremeter ranges definition based on cumulative ratios (right)

<u>**Catalogue of functional scenarios:**</u> By applying the same methodology to each of the scenarios in Figure 8, sets of scenario-dependent foreseeable parameter ranges are developed. This provides a complete catalogue of functional scenarios that can be applied for AD safety evaluation. The format of these scenarios is similar to those in the matrix in Figure 8, but includes lists of critical parameter and corresponding quantified ranges for each of the scenarios proposed.

Scenario database

The outcome of the overall process is envisioned as a database that provides the outcome of tests, but that also enables bidirectional traceability of the entire between the raw traffic monitoring data and the critical parameter ranges that define foreseeable conditions (Figure 13). Efforts to harmonize the development, maintenance, and accessibility to such database could lead to a common international database to support the a safe and global deployment of AD vehicles.

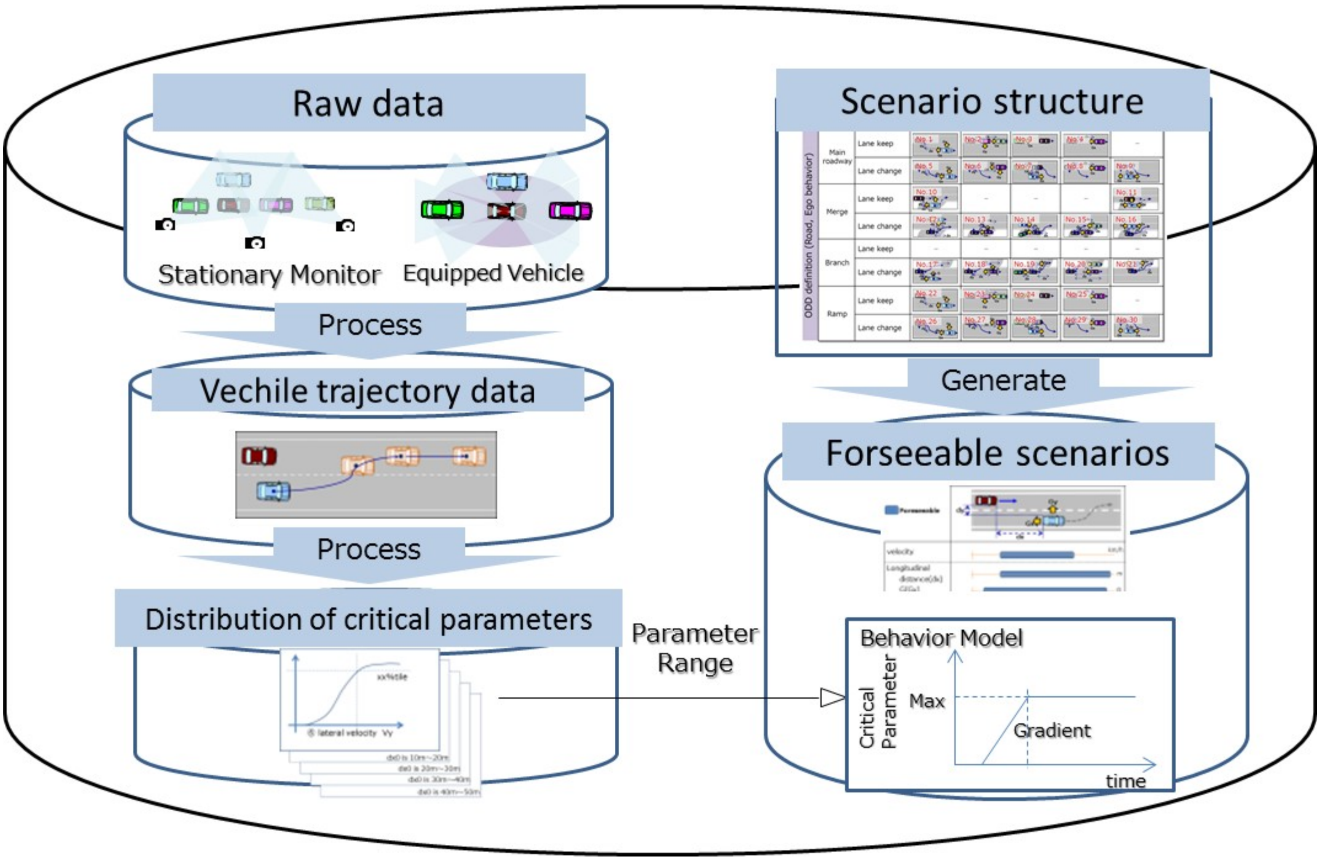


Figure 13 Database scheme with tracability from raw data to critical parameter Range

CONCLUSION

A safety assurance process for AD vehicles has been developed by JAMA and JARI under the auspice of the Japanese government and is hereby proposed. The proposal provides guidance on the overall safety assurance engineering process for Level 3+ AD systems under non-failure conditions on motorways, and on the methodologies to develop test scenarios and related criteria from real traffic monitoring data.

ACKNOWLEDGMENT

The results from a project financed by the Ministry of Economy, Trade and Industry of Japan have been utilized in this paper.

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DEVELOPMENT OF AN EMERGENCY CONTROL ALGORITHM FOR A FAIL-SAFE SYSTEM IN AUTOMATED DRIVING VEHICLES

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Paper Number 19-0101

ABSTRACT

This paper proposes the concept of automated driving vehicle failsafe system structure. It contains vehicle hardware and software structure design for automated driving vehicle failsafe system. Moreover, it handles the contents fail detection, fault-tolerant control, and emergency braking strategy in case there is no driver intervention in the fail condition of automated driving vehicle. According to the 2017 'AUTOMATED DRIVE SYSTEM 2.0: a vision for safety' report released by the NHTSA, it states that deployment of the crash avoidance system is essential to switch to a minimum hazardous condition in the event of a problem with the self-driving vehicle, or the system cannot operate safely. First, the method used to build the hardware & software of the vehicle was based on the guideline of 'AUTOMATED DRIVE SYSTEM 2.0: Section 1 fallback (Minimal Risk condition)' report released by NHTSA. Second, a method of an algorithm is sliding mode control based fault tolerant control and emergency deceleration control which designed to target SAE International standard J3016 autonomous driving phase 4: automated driving system perform ass aspects of the dynamic driving task, even if a human driver does not respond appropriately to a request to intervene. In this paper, to meet the requirements of autonomous driving phase proposed by SAE International standard J3016 phase 4 and NHTSA safety standard, the hardware configuration was created to ensure that the automated driving vehicle could perform the given task without proper driver intervention. In detection part, hardware (Actuator, Sensor, CAN signal, Upper&Lower controller) and module based failsafe diagnosis method and algorithm were proposed to detect fail condition. In decision and control part, when a failure of an automated driving vehicle is diagnosed, and no driver intervention was detected, the automated driving vehicle failsafe phase is a move to the system error. In the phase of the system error (lower controller), proposed methodologies are utilized. Automated driving vehicle experiments have demonstrated the algorithms as mentioned earlier and failsafe structure. First of all, it is true that not many papers and studies have been done on the failsafe system of an automated driving vehicle. NHTSA's safety report of an autonomous vehicle only contains a "suggestion" that says, "It is a good thing to do this," and has not yet created a rule. However, this paper proposes an automated driving vehicle failsafe system that is not commercialized but has been configured to meet NHTSA's requirements to take into account safety. The proposed failsafe system is applied to the automated driving vehicle, and the vehicle experiment was completed with the proposed algorithm. The proposed system is considered to be very compatible with the subject of the technical session by suggesting the system that meets the NHTSA standards as well as testing control and emergency systems targeted automated driving vehicle phase 4.

INTRODUCTION

Autonomous vehicle research aspect of failsafe and a fallback system is a very necessary and important study. Autonomous vehicles are composed of various sensors, computers, actuators and other types of equipment, and these equipment are configured to communicate together. In terms of fault diagnosis, each of them also needs real-time monitoring and also needs maneuver to be configured in the event of a failure. The algorithm proposed in this paper is an algorithm in the control part that makes an emergency stop when the fault is determined by fault diagnosis system when there is no driver intervention. The control classification was divided into two control categories, longitudinal control, and lateral control. Even if an error occurs that vehicle does not receive normal data from the upper controller that designed to recognition and judgment components of the autonomous driving system, the proposed algorithm only uses the vehicle's chassis information to provide a way for autonomous vehicles to respond safely. The vehicle hardware configuration is divided into upper controllers that responsible for recognition and judgment part and lower controller responsible for control of a vehicle. The lower controller consists of very robust hardware that allows for the safe longitudinal and lateral control in the event of errors in the upper controller.

Therefore, during the autonomous driving phase proposed by SAE International, level 4 suggests: the driving mode-specific performance by an automated driving system complete driving task, even if a human driver does not respond appropriately to a request to intervene.

Figure1. Waymo vehicle redundant Safety-Critical Systems. [1]

The hardware configuration was configured so that the autonomous vehicle could perform the failsafe system task without proper driver intervention. Although there are not many prior studies on the fault diagnosis system of autonomous driving systems was completed, the development of the failure diagnosis system of non-automated vehicles has already been carried out in terms of the failsafe system. YH.J developed the vehicle sensor fault diagnosis and acceptance algorithm and conducted the residual and adaptive threshold fault diagnosis without additional hardware. [3] KS. O conducted a study on the predictive fault diagnosis algorithm using sliding mode observers. [4] Advanced research in failsafe and system construction methods was consulted by overseas automotive OEMs. Google Waymo self-driving vehicles have applied fallback systems. Figure1. is Waymo safety-critical system description. Waymo vehicle's redundant system composed of backup computing, backup braking, backup steering, and a backup power system. [1] Similar to Google Waymo, CRUISE has a backup computer, backup actuator, signal communication redundant and data accumulation system. [2]

HARDWARE-BASED FAIL DETECTION CLASSIFICATION

In this chapter, mainly introduce module based classification of an autonomous vehicle fail detection and maneuver system. Hardware divide into Actuator, Sensor, Upper controller, CAN network and Lower controller. Actuator classifies as steering and throttle/brake. Sensor part composed of Lidar, Radar, and Vision (mono camera). The upper controller contains logic for perception and judgment of entire autonomous driving algorithms and calculates at regular intervals and transmits the calculated values to the lower-controller over real-time communication. CAN communication refers to the overall communication of the vehicle, including many sensors and actuators, vehicle inter communication, and uses a method to conduct real-time monitoring of their values. The Lower Controller consists of algorithms that calculate the relative sub-controller of the overall configuration, the algorithm for path tracking, or the control input that enters longitudinal control in the event of failure.

Sensor fail detection

The hardware fault detection method of the sensor is shown as Figure2. The manufacturer sends a corresponding fault signal from the sensor itself in the event of a fail. Delphi's radar has signals that can find many faults such as sensor communication error, sensor status failed, status blocked, and status over temperature, etc. Communication settings allow users to read the appropriate information. The figure 2. b) is about Ibeo LUX Ridar error and warning messages. Error contents internal error, a motor error, temperature rise, data loss, internal communication error, incorrect scan data, etc. The warning signal that is sent to the user can receive error messages such as internal communication, temperature increase, etc.

4E0	CAN_TX_COMM_ERRO R	Indication that the sensor has detected a communication error	False/True	bool	0: False 1: True	False	50ms	MMR
4E1	CAN_TX_XCVR_OPERA TIONAL	Sensor Status Radiating 0 = not radiating 1 = radiating	0 to 1	n/a	1	0	50ms	MMR
4E1	CAN_TX_INTERNAL_E RROR	Sensor Status Failed 0 = not failed 1 = failed	0 to 1	n/a	1	0	50ms	MMR
4E1	CAN_TX_RANGE_PERF _ERROR	Sensor Status Blocked 0 = not blocked 1 = blocked	0 to 1	n/a	1	0	50ms	MMR

6.1 Error register 1

Bytes	LUX error	Description	Comment
Bit 0	E-SP	internal error	contact support
Bit 1	E-Motor_1	motor fault	contact support
Bit 2	E-Buffer_1	scan buffer transmitted incompletely	decrease scan resolution/frequency/range; contact support
Bit 3	E-Buffer_2	Scan buffer overflow	decrease scan resolution/frequency/range; contact support
Bit 4	E-Meas_1	APD voltage failed	contact support
Bit 5		reserved	
Bit 6		reserved	
Bit 7		reserved	
Bit8…9	E-Temp	Bit 9: APD Over Temperature Bit 8: APD Under Temperature Bit 8 and 9: APD Temperature Sensor defect	provide cooling provide heating contact support
Bit 10	E-Motor_2	motor fault	contact support
Bit 11	E-Motor_3	motor fault	contact support
Bit 12	E-Motor_4	motor fault	contact support
Bit 13	E-Motor_5	motor fault	contact support
Bit14…15		reserved	

6.2 Error register 2

Bytes	LUX error	Description	Comment
Bit 0	E-IF_internal_1	no scan data received.	contact support
Bit 1	E-IF_internal_2	internal communication error	contact support
Bit 2	E-IF_internal_3	incorrect scan data	contact support
Bit 3	E-Configuration_1	FPGA not configurable	contact support
Bit 4	E-Configuartion_2	incorrect configuration data	load correct configuration values
Bit 5	E-Configuration_3	configuration contains incorrect parameters	load correct configuration values
Bit 6	E-Timeout_1	data processing timeout	decrease scan resolution or scan frequency
Bit 7	E-Timeout_2	reset the computation of the environmental model	contact support
Bit8…15	reserved		

6.3 Warning register 1

Bytes	LUX warning	Description	Comment
Bit0	W-CMD	internal communication error	
Bit1	W-Range_1	internal warning	
Bit2	W-Range_2	internal warning	
Bit3	W-low_temperature	temperature too low	warning of insufficient temperature
Bit4	W-high_temperature	temperature too high	warning of exceeding temperature
Bit5	W-Motor_1	internal warning	
Bit6	W-Motor_2	internal warning	
Bit 7	W-Sync	synchronization error	check synchronization- and scan frequency
Bit7…15	RES 7…15	reserved	

6.4 Warning register 2

Bytes	LUX warning	Description	Comment
Bit0	W-IF_CAN	CAN Interface blocked	check CAN bus and CAN connection
Bit1	E-IF_ETH	Ethernet Interface blocked	check Ethernet connection
Bit2	W-CANdata	incorrect CAN message received	check CAN data
Bit3	W-IF_internal_1	incorrect scan data	contact support
Bit4	W-ETHdata	unknown or incomplete data	check Ethernet data
Bit5	W-Command	incorrect or forbidden command received	check command
Bit6	W-Flash	memory access failure	restart ibeo LUX, contact support
Bit7	W-Overflow_1	internal overflow	contact support
Bit8	W-EgoMotion	vehicle data update missing	check CAN vehicle data
Bit9	W-Mounting Position	incorrect mounting parameters	correct mounting position according to OM
Bit10	W-CalcFrequency	no object computation due to scan frequency.	set the scan frequency to 12.5 Hz to receive objects
Bit11…15	reserved		

Figure2. a) Delphi Radar error message b) Lidar IBEO LUX error message[13]

Communication & controller fail detection

Inside the vehicle, communication is via the CAN bus (Controller Area Network) communication protocol is a standard communication specification designed to enable multiple devices to communicate with each other without a host computer. In order to detect errors in CAN signals, it is important to identify characteristics of CAN signals. Using the characteristics that the last value in the event of CAN failure is maintained by the host controller, utilized PC LabVIEW signal processing program, which is a higher control of an autonomous vehicle, can recognize an error about a CAN state that is judged to be a CAN error when the same value is received. The LabVIEW program itself can also detect errors on the CAN signal using a virtual instrument (VI) that detect for CAN errors. VI could find an error where the internal CAN state value is fixed. The upper controller refers to a PC and the lower controller (micro-autobox) that is responsible for control. Fault finding system that recognizes if one system fails while the PC to autobox system sends and receives data over CAN communication in real time.

FAILSAFE CONTROL

In this chapter, mainly address concept of failsafe control and reason of study. The main purpose of this part is to meet the requirements of SAE International level 4 as figure3. the control part that makes an emergency stop when there is no driver intervention after the failure determined by the algorithm.

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure3. SAE International standard J3016, Levels of vehicle automation

Failsafe control description The control part is divided into the longitudinal and the lateral part. Offer a way for autonomous vehicles to respond safely, using the vehicle's chassis information only, even if there is no information on the upper control part, i.e., the recognition and judgment part. The system error situation defined in this paper means network communication is blocked. In this situation, the last value in CAN network is only useful information. A failsafe module proposed in this paper utilized the unique phenomenon of system error and used that useful information to predict and control. System error – supervisor part contains prediction contents. The method used for longitudinal control is to calculate the safe driving distance in real time and transmit to reference deceleration model, and reference model calculates reference distance and reference velocity model for sliding mode control based deceleration and stop the algorithm. It is possible to make a stop within a safe distance through the above method. Lateral control consists of an algorithm that only uses the vehicle chassis information. This algorithm uses last information (desired path) of the upper controller to follow the path using DR to the lateral control algorithm.

The entire module was composed of the failure detection part that finds the failure of the total module, the failure detection part that carries out the classification for the failure, and the control model that is responsible for controlling deceleration with limited information.

Figure4 is hardware concept of the autonomous vehicle including the failsafe module. Considering autonomous vehicle hardware structure, the failsafe module was configured under normal circumstances, the algorithms of the perception, decision, and control algorithm operating in the upper controller. In order to prepare for a fault situation, the algorithms of the prediction in a fail-safe module using information from the upper controller calculate prediction algorithm in real-time. If an error is detected by the error-diagnosis module and no driver intervention is determined, the final information is used to predict and control. The last safety distance (in normal situation information) received from the upper controller is used in two ways. In the lateral direction, the dead reckoning algorithm will be used to drive the safety path, and in the longitudinal direction, sliding

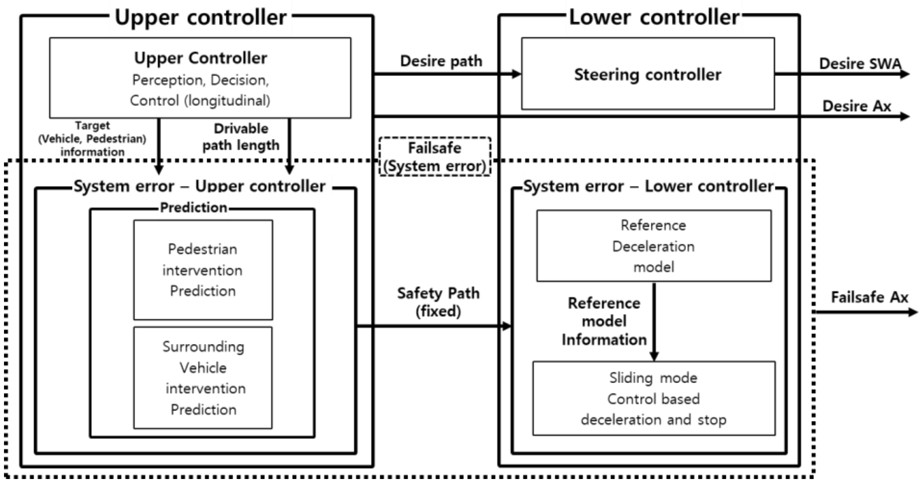


Figure4. Failsafe hardware concept diagram

mode control based deceleration and stop algorithm will be performed.

Methodology in this section, mainly describe System error situation used algorithm. One is defining reference deceleration model another is sliding mode control based deceleration and stop algorithm. The reference deceleration model [1] was determined by the general driver deceleration data which considering driver safety and ride comfort. The first-integrated velocity model and secondary integrated station model were used to construct an algorithm for stopping at safe distances. Pictures and formulas for longitudinal acceleration model, a longitudinal velocity model, and longitudinal distance model. V_x is initial velocity, a_m is maximum used deceleration, θ ($\theta = t/t_d$) is time ratio, t_d is deceleration time, m is a model variable parameter, r ($r = \frac{(1+2m)^{2+\frac{1}{m}}}{4m^2}$) is model parameter. Define a time-varying sliding surface $S(t)$ by the scalar equation $s(x;t)=0$, where $s(\mathbf{x};t) = e \cdot \left(\lambda + \frac{d}{dt}\right)^{n-1}$ and λ is a strictly positive constant. In this controller n =2 and he problem of keeping the scalar $s(t)$ at zero can be achieved by choosing proper control input u, the outside of $S(t)$, $\frac{1}{2}\frac{d}{dt}s(t)^2 \le -\eta |s(t)|$ and let equation $s(\mathbf{x};t) = 0$.

$$e(t) = S_{ref}(t) - S_{vehicle}(t) \qquad (1)$$

$$s(t) = \dot{e}(t) + \lambda \cdot e(t) \qquad (2)$$

$$V(s(t)) = \frac{1}{2}s(t)^2 \qquad (3)$$

In (1) $e(t)$ is an error between the reference station and vehicle station. (3) is Lyapunov function. Differentiating the Lyapunov function

$$\dot{V}(s(t)) = s(t) \cdot \dot{s}(t) \qquad (4)$$

For a stable system, the derivative of the Lyapunov function should be negative.

$$\dot{V}(s(t)) = s(t) \cdot \dot{s}(t) = -K \cdot |s(t)| < 0 \qquad (5)$$

$$\therefore \ \dot{s}(t) = -K \cdot tan(s(t)) \qquad (6)$$

$$\dot{s}(t) = \ddot{e}(t) + \lambda \cdot \dot{e}(t) = -K \cdot atan(s(t)) \qquad (7)$$

$$u_{eq} = a_{x,ref} - \lambda \cdot \dot{e}(t) - K \cdot atan(s(t)) \qquad (8)$$

design (2) sliding surface. Design sliding surface and calculate control input (8) tracking sliding surface. Control input u_{eq} is a longitudinal acceleration to vehicle SCC module.

Vehicle SCC (Smart Cruise Control) module description SCC (Smart Cruise Control) module is the ADAS system of Hyundai Motor Company. Through the communication operation, longitudinal acceleration, which is the control input put into the SCC module. SCC module is a module that considers safety and ride comfort of drivers. If longitudinal acceleration or deceleration is inserted into the module, the actual input value and vehicle reacts has a time delay. To analyze the characteristics of the delay conducted SCC module delay test. The test method verifies the characteristics of the SCC module by inserting the deceleration value into the module as input during vehicle accelerates and cruising.

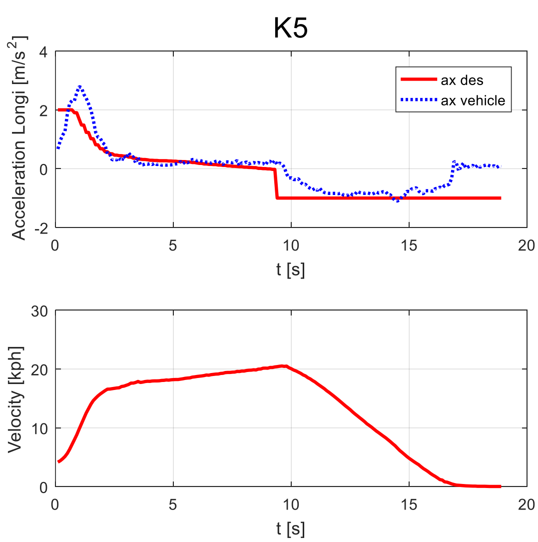
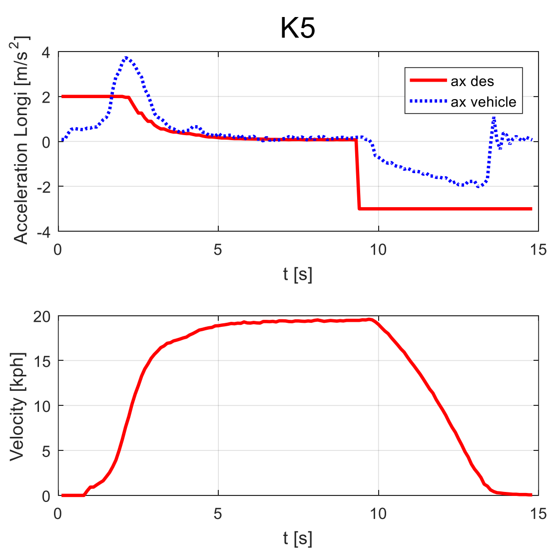


Figure5. K5 deceleration test ($-1m/s^2$ ***, 20kph)***



K5 deceleration test ($-3m/s^2$ ***, 20kph)***

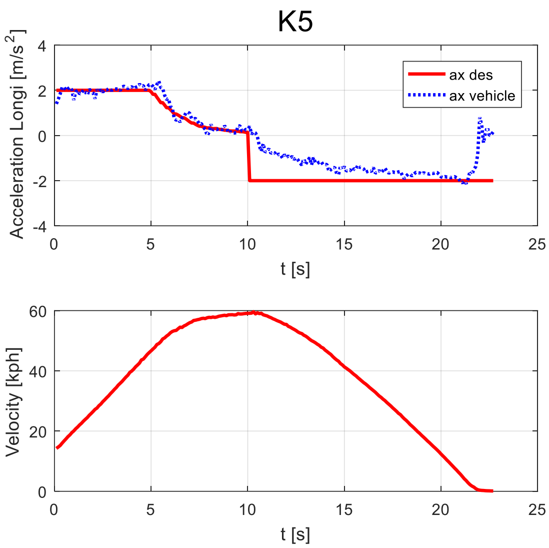
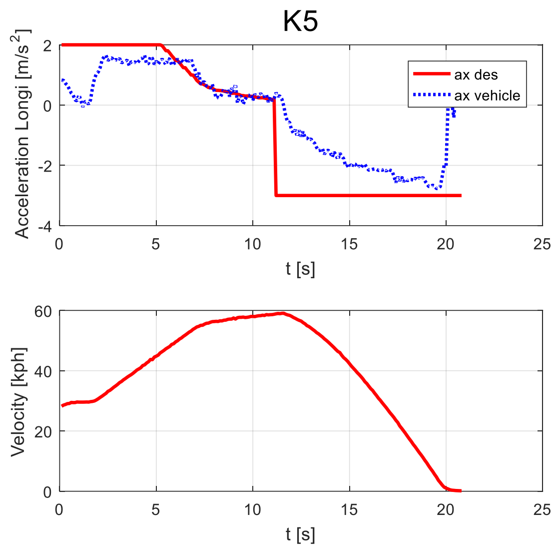


Figure6. K5 deceleration test ($-2m/s^2$ ***, 60kph)***



K5 deceleration test ($-3m/s^2$ ***, 60kph)***

If the reference model referred to in chapter 'Methodology' is inserted directly into the vehicle SCC module, it can be safely stopped within the specified distance of a simple configuration without the use of other control methods. Therefore, the output of the reference station and reference velocity utilized as control input. As a result, the problem of delay in SCC module extension time resulted in a value different from the value of the reference model to the output of the vehicle. The following chapter is the result of multiple experiments and test data showing that the SCC module has the nonlinear characteristic.

As mentioned above, control inputs were applied in several situations to experiment with nonlinear characteristics of SCC module. The test scenario is set as follow. 1. 20km/h (minus one to minus five) deceleration to stop 2. 40km/h (minus one to minus three) deceleration to stop 3. 60km/h (minus one to minus three) deceleration to stop 4. Acceleration test

K5 vehicle deceleration test for check SCC module delay. Test content contains constant deceleration from $-1m/s^2$ to $-3m/s^2$ when vehicle velocity close to 20 km/h and 60km/h. From test get a conclusion about SCC module delay as follow. First, module exists time delay about 0.1second to 0.5second. Second, module deceleration control input is not severe so couldn't reach command input . In conclusion, the SCC module exists time delay and nonlinear model characteristic.

Sliding Mode Control based deceleration vehicle test For the failsafe control deceleration and stop vehicle test, the following methods were used to conduct the test. The whole vehicle test was conducted in autonomous mode, from beginning to end the experimental scenario was planned and conducted in low-speed area of 20km/h and 30 km/h. Figure7 shows that the vehicle has been tested on autonomous mode from stop → accelerate → stops. The first figure in Figure7 shows the vehicle accelerating to ACC mode up to 30 km/h and the sliding mode control based algorithm operating when failure occurred. The second figure is a comparison of the longitudinal acceleration of the vehicle and the control input (longitudinal acceleration) into the vehicle SCC module.

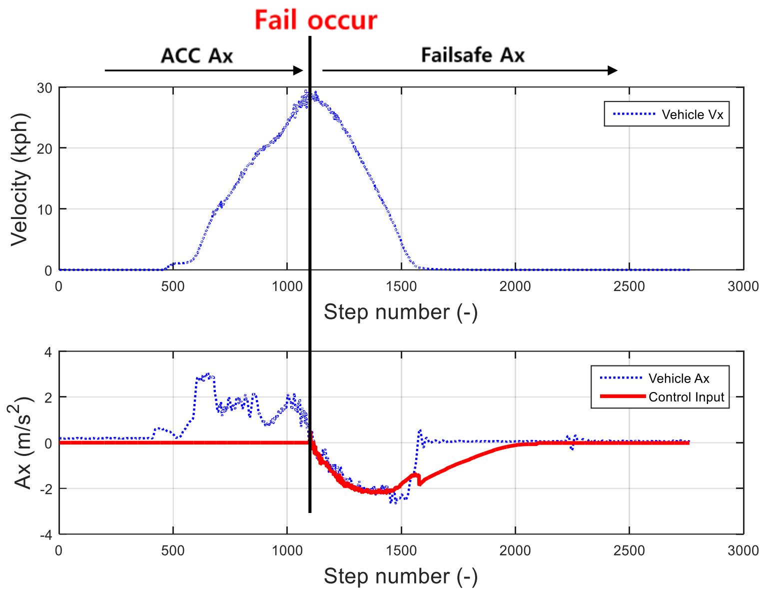


Figure7. Vehicle test scenario – Acceleration to stop

VEHICLE TEST RESULT

The fail-safe module described above chapter is applied to the autonomous vehicle as Figure8. As described in Figure8, a number of algorithm and method have been applied to the actual autonomous vehicle. The alarm system has been constructed to allow the driver to recognize the warning situation in autonomous vehicles. In perception part, 1) Internal CAN communication error in the vehicle, 2) CAN value holding error (for multiple CAN channels), 3) sensor hardware error. These error warning system has been constructed to alert the driver. The proposed automated driving control algorithm is evaluated through computer vehicle tests. In order to evaluate the proposed algorithm on a real test vehicle, Hyundai-Kia Motors K5 is used as a test vehicle platform. Figure 5 shows the test vehicle configuration. The proposed algorithm has been implemented on “dSPACE Autobox”, which is used for the real-time application and equipped with a processor board. The hardware components mentioned above communicate through a CAN bus.

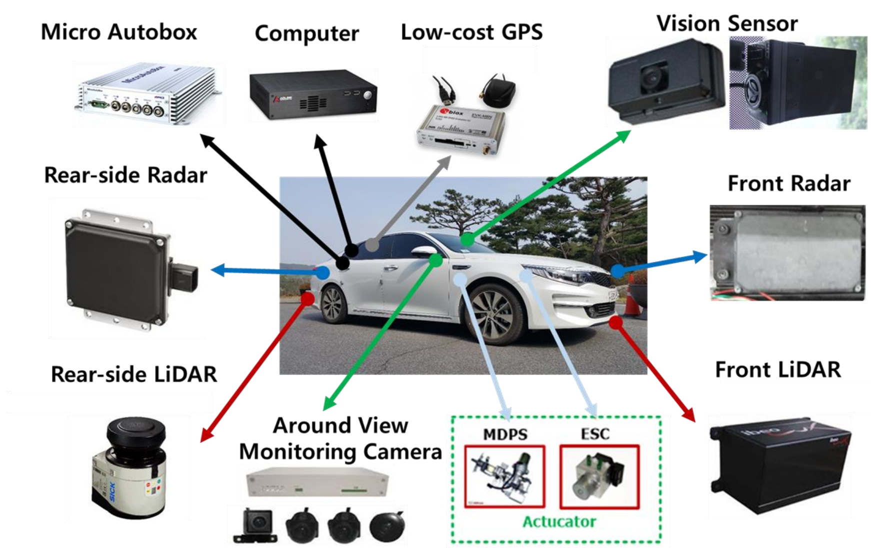


Figure8. Autonomous vehicle hardware configuration

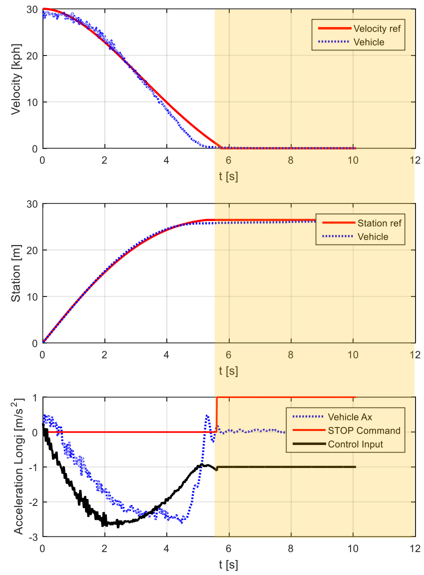


Figure9. Vehicle test result – (a) Velocity (b) Station (c) Vehicle and Control input

Figure9 is vehicle test result near 30km/h. (a), (b) and (c) are respectively the vehicle longitudinal velocity and reference model velocity profile, vehicle station and reference model station, vehicle acceleration and control input, the experiment result shows that the sliding surface follows well through the control input. The yellow section addresses overload problems on SCC modules rather than algorithmic stops and consists of stopping with constant deceleration as the speed decreases for module safety.

CONCLUSIONS

In this paper, in order to meet the requirements of autonomous driving phase proposed by SAE International, the hardware configuration was made to ensure that the driver could perform the autonomous vehicle task without driver proper intervention. In detection part, hardware (Actuator, Sensor, CAN signal, Upper controller, Lower controller) and module (Steering, Throttle/Brake, Lidar, Radar, GPS, CAN signal, CAN status, Chassis CAN) based failsafe diagnosis method and algorithm were proposed to detect fail situation. In decision and control part, when a failure of an autonomous vehicle is diagnosed and no driver intervention was detected, autonomous vehicle failsafe phase is a move to system error in figure4 in the phase of the system error (lower controller), reference station model and reference velocity model was calculated in real-time. Sliding mode controller based deceleration and stop algorithm tracking designed sliding surface. The effectiveness of the proposed automated driving fails situation deceleration algorithm has been evaluated via test-data based simulations and vehicle tests. From the results, it has been shown that the proposed algorithm can provide the robust performance in low speed (20,30kph) condition.

* This work was supported by National Research Foundation of Korea(NRF) grant funded by the Ministry of Science, ICT & Future Planning (NRF-2016R1E1A1A01943543). This work was supported by the Technology Innovation Program (10079730, Development and Evaluation of Automated Driving Systems for Motorway and City Road) and driving environment) funded by the Ministry of Trade, Industry & Energy (MOTIE, Korea). This research was supported by the Korea Ministry of Land, Infrastructure and Transport. It was also

supported by the Korea Agency for Infrastructure Technology Advancement (Project No.: 18TLRP-B117133-03).

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DEVELOPMENT OF SAFETY EVALUATION SCENARIOS FOR INFRA-COOPERATED AUTOMATED VALET PARKING SYSTEMS

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Paper Number 19-0123

ABSTRACT

This paper presents an evaluation procedure for an infrastructure based automated valet parking system. Because parking is one of the difficult and complicated tasks for drivers, park assistance system(PAS) has been already developed and commercialized by several auto-manufacturers. As a further step for PAS, researchers are focusing on automated valet parking system which is a fully automated system of PAS and periodically demonstrated their automated parking system. However, from an institutional point of view, evaluation standard and scenarios for automated parking system are progressing slowly compare to the automated driving. Because of specialty that in valet parking system, driver has to get out of the vehicle, most of the developers can not mass produce the system by legal issues. Thus, the necessity of evaluation procedure for parking system rise. Considering many automated valet parking systems are designed with digital map or infrastructure. Thus, in this paper, automated valet parking system cooperating with infrastructure is focused.
To design the evaluation process for automated parking, we divided the parking situation into two sides. 1) Nominal parking process, which is a static obstacle avoiding case related to static factors. 2) Complicated parking process, which is avoiding not only static obstacles but also moving obstacles such as pedestrians. As a valet parking is a very sequential service, to design evaluation items for nominal parking, we considered a procedure of manual parking and divided valet parking process into three different stages. 1) Driving in the parking lot while moving near to the parking space. 2) Parking to the aimed space. 3) Parking out from the space. Finally, the component of nominal parking scenario classified as static factors to test basic parking performance of the target vehicle and addable evaluation scenarios listed up as dynamic factor which can reproduce the complicated and frequent situation that can happen in the parking lot by combining with the nominal scenario. Both the nominal scenario and additional scenarios are organized as an evaluation matrix.

INTRODUCTION

In recent years, research has been carried out vigiriously about advanced driver assistance systems (ADAS) and autonomous vehicle. One of those automated driving technology, automated parking and parking assistant system are one of the close to mass production technology since parking is considered as troublesome and time-consuming task in driving. Thus various of configuration of sensor set for parking assistance[1-5] has been researched, furthermore, some car-makers, such as BMW and Volvo, periodically demonstrated their automated parking system. Now the researchers are aiming the fully automated parking system as a further step of PAS.
At the same time, the regulation and test procedure for active safety also have been researched including well known ADAS systems such as Adaptive Cruise Control (ACC), Traffic Jam Assist (TJA), Lane Keeping Support

(LKS), Lane Change Assist (LCA), Blind Spot Detection (BSD) and Advanced Emergency Braking (AEB)[6,7]. And the target system of the regulations and test protocols has been extended to automated driving and some legal issues hav been eased such as license system that allows automated vehicle driving in some area in normal road. But still, in a sight of automated parking technology, compare to automated driving, some legal issues are left to test and commercialize. Similarly, the research about test procedure for automated parking has plenty of works to do.
In case of Korea, recently standard about the definition of automated valet parking system had been released[8] and some test procedure of KNCAP related to parking situation such as AEB and rear-side access alarming system had been also already released[9]. But still, the detail factors to be consider to test the actual valet parking system has to be defined and have legal issues to evaluate the test procedure. There are some legal amendment for the automated driving on highway and urban road, valet parking has more issues about operating the acceleration/deceleration and steering system of the vehicle without the driver. And the automated valet parking system is still in develop, there are various automated parking related systems from level 2 to 4. Thus, the test scenario would be better if it can manage the automaed parking system widely according to the level or technical coverage of the test target's system.
In this paper, the infra-cooperated valet parking system divided into lower level maneuver based on the sequence of valet parking. The typical factors which should be considered in a sight of parking area's enviroment and situation are summarized. Then, we present the actual test case generation by cobiming the factors that can manage based on test site and test target system's needs and coverage. Last of all, the proposed test scenario is verified via computer simulation.

SEQUENCE OF INFRA-COOPERATED VALET PARKING TEST

To evaluate the valet parking test scenario, as a first step, the sequence of the parking should be defined. Excepting the static environment conditions such as shape of target parking lot, the entire valet parking service can be devided into two major items, parking and exit. Parking is a sequence that starts from the predefined zone and ends when the vehicle is parked in empty slot. Compare to parking, exit is a sequence that gets out from the parked slot and comes back to the predefined zone where the vehicle started the parking sequence. In short, exit and parking are the opposite process. More specific items and situation are shown in fig. 1.

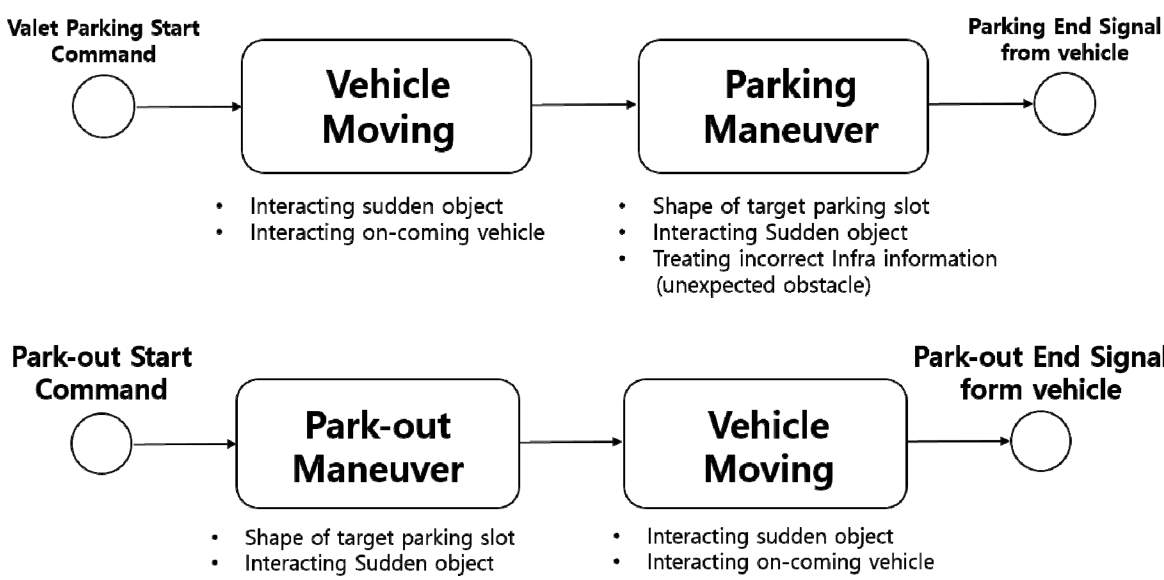


Figure1. Sequence of valet parking service.

Low-level Components for valet parking sequence

The two sequences, parking and exit can be also divided into two phases each. For both sequences, they have same purpose that the vehicle should move from starting point to the end point. The only difference is the fact that parking has to park in, and exit has to get out from the parked slot. Thus they have common phase, the vehicle moving phase. To consider their difference, parking maneuver phase and park-out maneuver phase are divided. In summary, the parking sequence is consisted with vehicle moving phase and parking maneuver phase and the exit sequence is consisted with park-out maneuver phase and vehicle moving phase.

Vehicle moving phase When the vehicle is in vehicle moving phase, it is very similar to the urban road driving cases. The only thing to do is to drive within a designated area, watch out for a collision, and move the vehicle to its destination. To specialize in parking area, vehicle can meet sudden pedestrian or parked out vehicle while driving parking area. Also, unlike to normal driving cases, facing with on-coming vehicle can also occur when two or more vehicles driving in parking area.

Performance evaluation In vehicle moving phase, whether the vehicle is driving within a designated area is the basic object of the phase. The boundary of the designated area is line that divides the parking slot and driving area in this case. It can be easily checked with the trajectory of the vehicle with known vehicle size, or the surround view camera images of the vehicle. Addable scenario item to this phase could be sudden obstacles such as pedestrian or parked out vehicles, which is similar to the urban AEB test scenarios[6]. In parking area, the vehicle should driving their velocity under 10kph, thus the test scenario case only needs for the vehicle speed 10 kph. For the on-coming vehicle interacting case, the subject vehicle has to leave enough space when the on-coming vehicle detected. The width of driving area is at least 6m space in law, thus the half of the space should be opened to on-coming vehicle.

Parking & Park-out maneuver phase Parking maneuver phase is a phase that park the vehicle into the parking slot without collision to the surroundings. Park-out maneuver phase is a phase that get out from the parked slot, which is directly reverse process of the parking. Although these two phases are separated because their region to watch out or consider is different, when we think ideal cases, excepting the moving obstacles, the two sequences have very similar actions, design collision-free path to static surroundings such as wall or other parked vehicles and control the vehicle to track that path. As addable scenarios, pedestrians walking near the selected parking slot, or other moving vehicle in parking area can be considered.

Performance evaluation As the parking and park-out maneuver phase are focusing on the collision and control performance, the major performance to be checked is that the vehicle totally get in to the parking slot or get out from the parking slot without any collision. For parking maneuver, when vehicle ends the parking, the vehicle should be fit in the parking slot well, which means the vehicle should not interfere the parking line. For both parking and park-out phases, the collision should not occur in their progress. For only static obstacle cases, checking the vehicle's trajectory or surround view images of the vehicle would be fine. For the moving obstacle cases, especially for the pedestrians, similar to AEB test, design the expected collision point and check the vehicle actually stops for each cases. For other driving vehicle case in parking area, the test scenarios are representable using reverse case of the rear-side access alarming system test[9].

CONSIDERING FACTORS FOR CO-INFRA VALET PARKING TEST

As shown in the previous chapter, infra cooperated valet parking test, the test condition can divided into static environment condition and dynamic environment condition. Static conditions usually contains weather, road shape, especially for the co-infra parking scenarios, it can be extended to other factors such as surrounding object placement near the target parking slot, shape of the parking slot. The considered static environment factors are as follows in table 1.

Structural Environment The valet parking test cannot held without the parking lot. Thus the structural factor is one of the considerable element in valet parking. The structural elements starts with whether the parking area is outdoor or indoor. If the parking area is placed outside, than the floor of the area would be automatically 1st floor only case and the global navigating system such as GPS would available. On the other hand, for multi-floor parking area, which is often seen in skyscraper or underground parking lot, the vehicle has to overcome the localization or indoor position problem itself. In short, the structural element is composed with whether the parking area is indoor or not and the parking lot has multi-floor or not.

Shape of target parking slot Shape of the target parking slot is one of the typical condition in parking. Especially for the parking or park-out maneuver, it is directly related to their trajectory generation. And this is the factor that parking has differentiation from driving. There are typically three different types of slots, one is perpendicular parking which is often called as T-parking. Another type is parallel parking, which is often used in road parking. And the last type is diagonal parking, which is usually placed in large parking lot area. The slot's shape condition can be affected from both valet parking system maker and test site. Test sites often have most of them for offer various test cases, but the valet parking technology is still in developing, hence the system or algorithm makers might have limits to their available range in shape type.

Table1.
Static factors of valet parking scenario.

<table>
<tr><th rowspan="2">Structural element of parking lot</th><th colspan="2">Geometric Positional Condition (G)</th><th colspan="2">Floor type (F)</th></tr>
<tr><td colspan="2">• (G-1) outdoor area (GNSS available)
• (G-2) indoor area (GNSS unavailable)</td><td colspan="2">• (F-1) Single floor case (floor movement X)
• (F-2) multi floor case (floor movement O)</td></tr>
<tr><th>Shape of target parking slot (S)</th><th>T parking
(S-T)</th><th colspan="2">Parallel parking
(S-P)</th><th>Diagonal parking
(S-D)</th></tr>
<tr><th>Object placement near goal (P)</th><td colspan="4">(P-1) only the target parking slot is empty
(P-2) two slots are empty in a row including target space
(P-3) more than three slots are empty in a row including target space</td></tr>
<tr><th rowspan="2">Correctness of Infra' s information</th><th colspan="2">Status of infra (I)</th><th colspan="2">Unexpected object in target space (O)</th></tr>
<tr><td colspan="2">(I-1) Normal (target space is empty)
(I-2) Error(unexpected obstacle in target space)</td><td colspan="2">• (O-1) full size vehicle
• (O-2) two wheeled car
• (O-3) parking cone
*this category only activates in (I-2) case</td></tr>
</table>

Object placement near goal Object placement near goal is the factor that defines the availability of the parking slots near the target slot before the system test starts. The graphical concept of this factor is shown in fig. 2. This category can be very minor change compare to the other categories, because if the valet parking system can solve (P-1) case, which is the only target parking slot is empty, then other cases like (P-2) and (P-3) are automatically available. Although the (P-1) is the most challengeable case among them in vehicle control side, but as for detecting the actual slot's area, (P-2) and (P-3) become more challengeable case cause the system need to detect the parking lot line and identify the target space among them. Thus, as for the test environments, this factor also has to be considered differently.

<u>Correctness of Infra' s information</u> The testing target system of this paper is infra-cooperating valet parking system. This means that when the total valet parking sequence starts, infra gives the target parking slot to vehicle, and vehicle moves to the point. In a side of testing the vehicle's valet parking system, this factor is considered to check the ability that the vehicle can overcome the wrong information from the infrastructure. When infra gives the information, there would be actually tow cases. First case is the when the information is true, means the slot's actual availability is same with the known information. In this case, there is no extra issues for the scenario and becomes the basic case. On the other hand, if the known information is inconsistent with actual information, that means there is unexpected objects in the target parking slot. The unexpected objects can be other parked full size or two wheeled vehicles, or just banned with parking cone for other issues such as repair work. The situation that the target slot is unavailable seems already enough for vehicle to react, but the vehicle should make a decision that the space is unavailable itself. Thus, similar to the object placement category different types of object represents different condition to detection system of the vehicle.

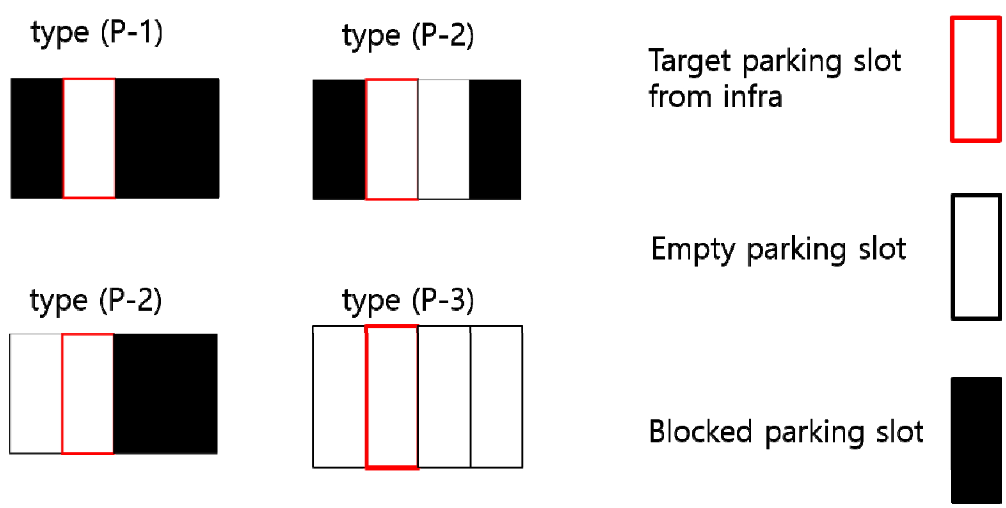


Figure2. Different object placement around target parking slot.

Table2.
Dynamic factors of valet parking scenario.

During vehicle moving phase	**pedestrian (H)**	**Park-out vehicle (J)**	**교행 vehicle (K)**
	(H-1) Adult(8 kph) (H-2) child (5 kph)	**(J-1) 5 kph** (J-2) 10kph	**(K-1) on-coming vehicle(10 kph)**
During vehicle parking& park-out phase	• **(E-1) adult pedestrian crossing the parking slot while in parking maneuver** • (E-2) child pedestrian crossing the parking slot while in parking maneuver • (E-3) other vehicle passing near the parking slot while in park-out maneuver		

Dynamic factors The above components are static factors that are predefined and maintained during for one test case. In contrast, the dynamic factors, in this case the moving objects, also can be represented in each test cases. Most typical moving objects in parking area are pedestrian and other moving vehicles. The dynamic factors can be listed in a similar table form above, which is shown in table 2. Here, we divide up the situations into two low-level component sequences that mentioned in valet parking sequence part. For each moving objects. Thus the factor (H-) and (J-) represents sudden moving objects while the subject vehicle driving the parking area. Factor (K-) shows the on-coming vehicle cases, and the factor (E-) gives the moving object during parking or park-out maneuver.

TEST CASE CONSTRUCTIION

From the previous two sector, we see that the system should be tested with total sequence level, and show the factors that majorly affects to the systems performance in a sight of autonomous valet parking vehicle. Still the valet parking system is in develop, for actual test, some factors can be considered and others are might not. Thus while constructing the actual test scenarios, firstly, define the systems coverage and divide the static and dynamic factors into the test cases. Table 3 and Table 4 shows one example of the test case generation and the following check list of each cases for one floor outdoor condition parking lot with all different type of parking slot shape.

Table3.
Test case/check list generation using static/dynamic factors.

Test case No.	Static Factor Condition	Dynamic Factor Condition
No.1	(S-T)-(G-1)-(F-1)-(P-1)-(I-1)	none
No.2	(S-P)-(G-1)-(F-1)-(P-1)-(I-1)	none
No.3	(S-D)-(G-1)-(F-1)-(P-1)-(I-1)	none
No.4	(S-T)-(G-1)-(F-1)-(P-2)-(I-2)-(O-2)	(H-1)-(J-1)-(E-1)
No.5	(S-P)-(G-1)-(F-1)-(P-2)-(I-2)-(O-2)	(H-2)-(J-2)-(E-3)
No.6	(S-D)-(G-1)-(F-1)-(P-3)-(I-2)-(O-3)	(K-1)-(E-2)

Test case no.	Check list
Common criterion	- Whether the vehicle keep driving in the designated area - Whether the vehicle fit-in the parking slot after parking - Whether the vehicle interfere the parking line in parking/park-out maneuver
No. 1	**- Common criterion only**
No. 2	**- Common criterion only**
No. 3	**- Common criterion only**
No. 4	**- Common criterion** - Whether the vehicle figure out and notive that the target slot is unavailable

	- Whether the vehicle properly stop and avoid collision with moving objects
No. 5	**- Common criterion** - Whether the vehicle figure out and notive that the target slot is unavailable - Whether the vehicle properly stop and avoid collision with moving objects
No. 6	**- Common criterion** - Whether the vehicle figure out and notive that the target slot is unavailable - Whether the vehicle properly stop and avoid collision with moving objects - Whether the vehicle make enough space for on-coming vehicle

In 6 test cases, the first three cases have no any dynamic factors and the other three test cases have dynamic conditions such as sudden pedestrian occurring. Although the test cases are generated based on the test target system's coverage, in order to system successfully perform the valet parking, test cases that only depends on static factors must be satisfied, in this case, test case no. 1-3. Common criterion shows the least conditions for system to be defined as valet parking system. As an extension of these cases, by considering dynamic factors, test case no. 4-6 shows whether the vehicle can react with some sudden objects or frequent situation when other moving objects are in the parking area. Thus the tested system can be differentiated their performance consider to the system that just doing basic operation of valet parking.

SIMULATION TEST RESULT

In this chapter, the simulation of the proposed test scenario is proposed. For this, valet parking algorithm which is presented in previous research is introduced in the first section. Using this valet parking algorithm, computer simulation was conducted using simulation tool MATLAB and Simulink.

Valet Parking Algorithm

In the study of Jeong[10], the reasearch proposed valet parking algorithm focusing on moving obstcle while driving in the parking area. The architercture of the test target algorithm is as follow in fig. 3. Based on the surrounding static/moving obstacle data and digital map, the algorithm infer the intention based on IMM filter and represent the drivable area in parking area by using potential field approach.

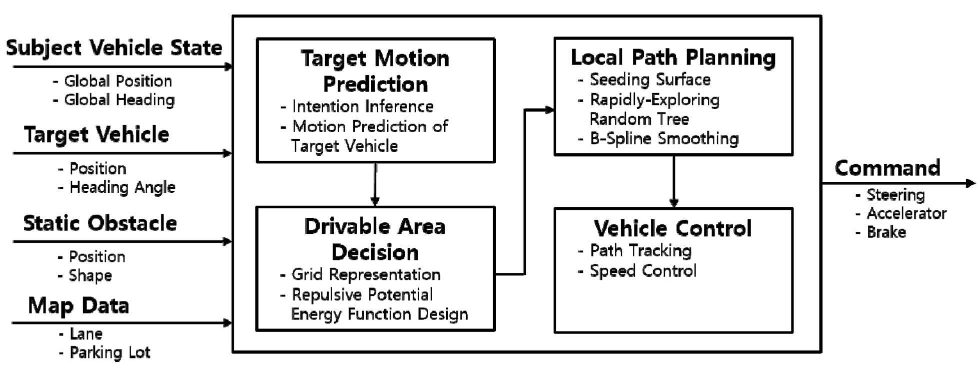


Figure3. Overall architecture of tested Automated Valet Parking

For the detail representation, two different potential energy function is used which is researched by Kim[11]. For the static obstalces or parking line boundary, cleareance based energy function is used which is in equation (1).

$$U_{rep} = \begin{cases} \min\left[U_{rep,\max} \, , \; k \cdot \left(\dfrac{1}{D} - \dfrac{1}{Q} \right)^2 \right] & if \;\; D < Q \\ U_{rep,\max} & else \end{cases}$$

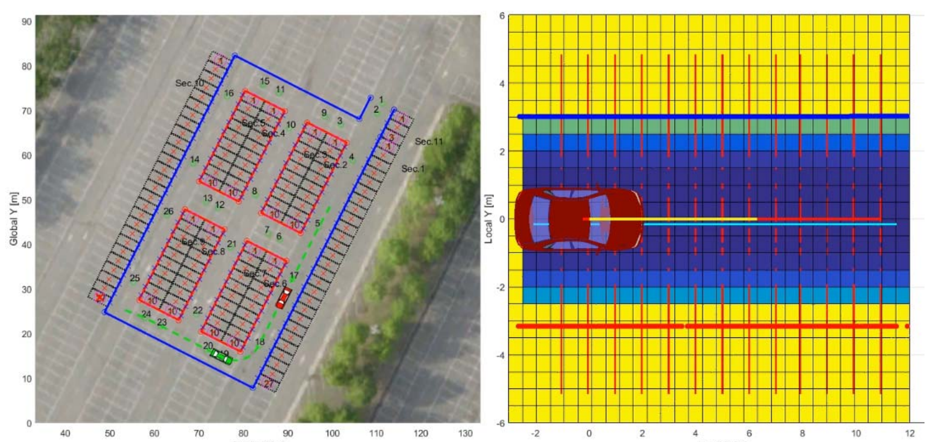
On the other hand, for the moving object, to imply the velocity information of the object, equation (2) is used.

$$U_{rep} = \begin{cases} k \cdot \exp\left(-\left(\dfrac{x_{r,p}}{\dot{x}_{r,p}} \right)^2 - \left(\dfrac{y_{r,p}}{\dot{y}_{r,p}} \right)^2 \right) & if \;\; \left\| \rho(x_{r,p}, y_{r,p}) \right\| < \rho_{long} \\ 0 & else \end{cases}$$

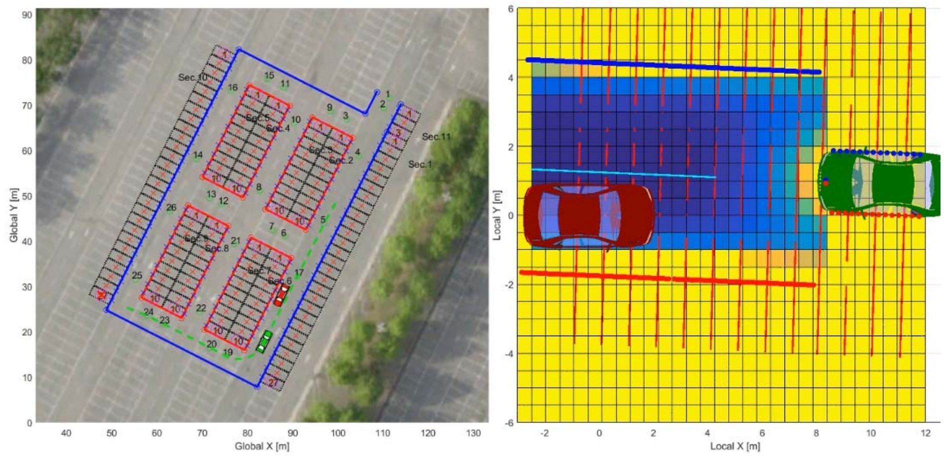
While in simulation, the surround representation result of this algorithm can also be used as check the actual collision occur or not for the test case.

Simulation Result

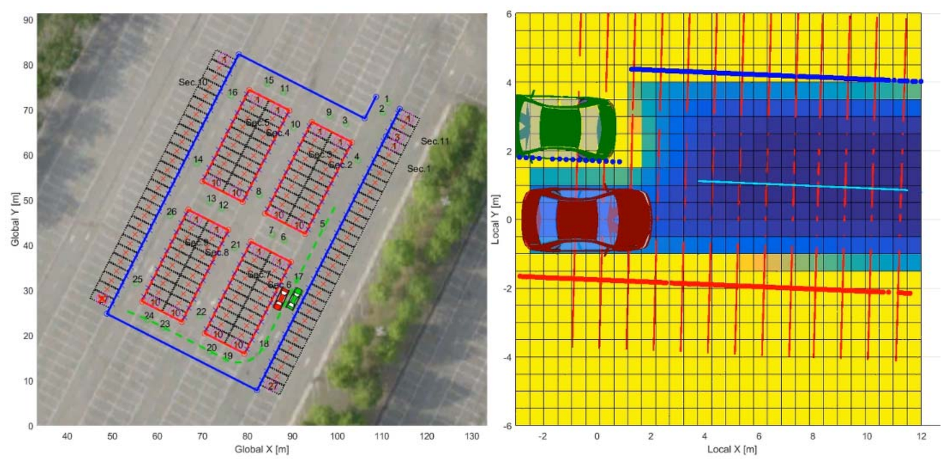
Computer simulation was conducted using simulation tool Carsim and MATLAB/Simulink. In this paper, the simulation result of total progress of Parking into T park slot including on-coming vehicle condition in a snap-shot image form.



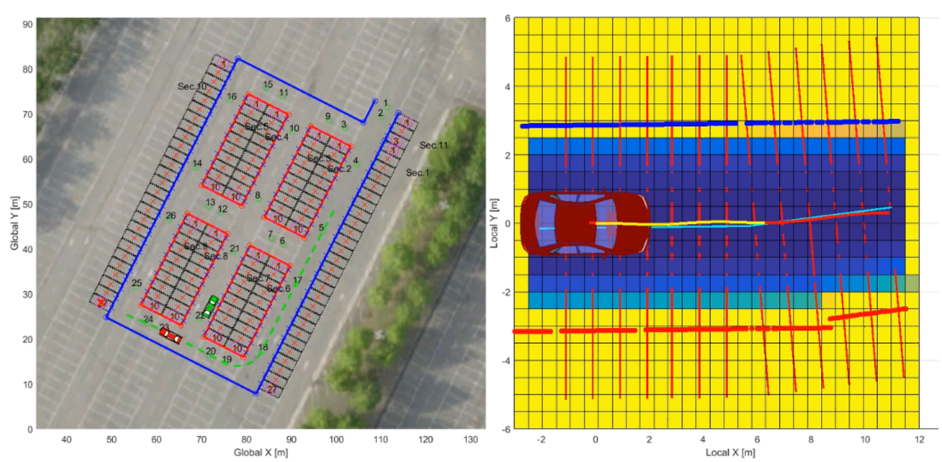
(a) Normal driving before meeting on-coming vehicle



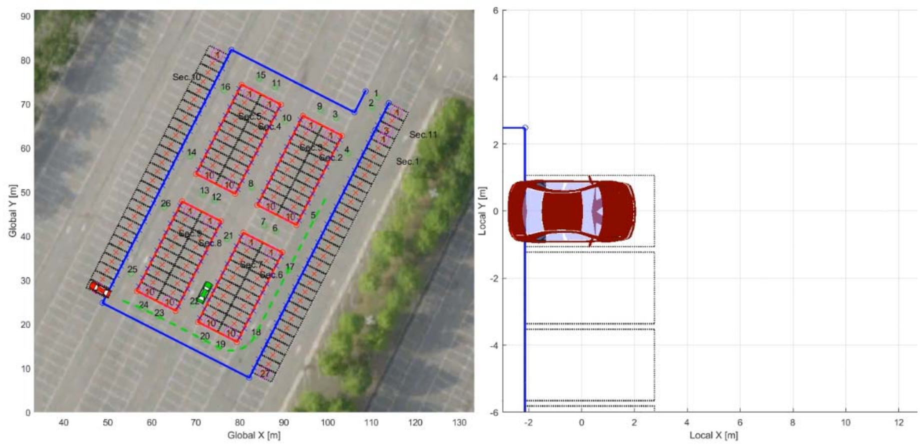
(b) Detect the on-coming vehicle & space generating on-coming vehicle



(c) Waiting for on-coming vehicle to pass



(d) Come back to global trajectory and keep move to goal



(e) Front side parking with fit-in left/right parking line of the goal

Figure4. Snap shot images of one example of valet parking simulation Testing condition with (S-T)-(G-1)-(F-1)-(P-1)-(I-1), (K-1)

Simulation Case: T- slot parking with on-coming vehicle The simulation result of the parking scenario in fig. 4. As the parking scenarios should check whether collision and interference occur or not, the simulation result proposed with graphical image of global situation to see the progress of total sequence and local coordinate of subject vehicle to check the collision or interference. The static factor condition is (S-T)-(G-1)-(F-1)-(P-1)-(I-1), which means outdoor parking lot with target slot shape T parking, and the information from the infra is correct. For the dynamic factor, (K-1) is applied before the subject vehicle enters the corner point of the global trajectory. The proposed images are mainly focusing on moment when the on-coming vehicle and subject vehicle met. The subject vehicle is shown as red vehicle and the on-coming vehicle is shown as green. Left images show the global position of both vehicle and right side images show the local path and boundary of the environment in local coordinate of the subject vehicle. As the result shows, the subject vehicle avoid the collision with the on-coming vehicle and finally parked into the target slot. Although the used parking algorithm had its coverage parking sequence, the scenario case can be applied as a partial test form.

CONCLUSIONS

In this paper, a procedure for evaluating scenarios for infra-cooperating valet parking system has been developed. The proposed test scenario divide the infra-cooperating valet parking with three sequential phases, vehicle moving, parking, park-out maneuver. To construct the factor matrix of the test condition, several frequent situation that can be face in parking lot area are list up and classified into static condition and dynamic condition. Then as a final step, test cases are generation step is suggested considering the test target system's coverage and the test site's condition, to manage both level 4 parking system and lower level parking assist systems. As an one example, one of the valet parking algorithm is applied with generated test case. The simulation shows that the proposed valet parking test scenario can be applied to one total functional sequence data and check whether the parking system works well including the performance of basic purpose

In order to develop the specific regulation such as rating criteria and detail procedure of each test scenario, additional vehicle experimental test should be conducted with various test cases applied to systems.

* This research was supported by the Korea Ministry of Land, Infrastructure and Transport. It was also supported by the Korea Agency for Infrastructure Technology Advancement (Project No.: 18TLRP-B117133-03); the Technology Innovation Program (10079730, Development and Evaluation of Automated Driving Systems for Motorway and City Road) and driving environment) funded By the Ministry of Trade, Industry & Energy(MOTIE, Korea); National Research Foundation of Korea(NRF) grant funded by the Ministry of Science, ICT & Future Planning (NRF-2016R1E1A1A01943543).

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DIFFERENT APPROACHES TO THE NEW REGULATORY CHALLENGES FOR CONNECTED AND AUTOMATED VEHICLES (CAV)

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Paper Number 19-0192

ABSTRACT

Automated Driving (AD) is foreseen to be one of the major social and technological challenges in the coming years. Many manufacturers are developing new models with cutting-edge functionalities, which are not included in the scope of the current regulatory framework. Apart from demonstrating their know-how and expertise on AD, their willingness to sell their AD models in the European market is accelerating the rule-making system. However, what is the roadmap for the European regulatory framework? Policy makers and regulatory bodies are pushing their boundaries at all levels (national and international) in order to introduce modifications in existing regulations. These regulations will enable the introduction of these new functionalities into the market. Without decreasing the standards of safety and security, the implementation of a clear and harmonized regulatory framework and approval process is extremely necessary.

The last amendments of the UN Regulation nº79 related to steering equipment or the creation of new standards such as the ISO 21448 regarding Safety and Intended Functionality (SOTIF) are examples of recent efforts from the regulatory bodies to achieve this goal. The aim of this paper is to show the state of the art of the regulatory framework regarding automated driving. In order to provide a thorough understanding of the forthcoming amendments and new standards, the different challenges that the European Commission (EC) / United Nations Economic Commission for Europe (UNECE) are facing will be analysed, as well as the different approaches to be considered by the international regulatory bodies.

Finally, as a result of this research, the conclusions will be presented as considerations and proposals for all players involved in this change of paradigm: users, manufacturers, approval authorities and technical services.

INTRODUCTION

The deployment of new advanced technologies and new needs in our society is resulting in a change of paradigm when talking about transport modes. This change of paradigm is resulting in new vehicle concepts, new business cases and new propulsion technologies. Nowadays, all manufacturers are developing models with more advanced functionalities, moving forward to more highly automated vehicles. New actors are also involved in these new vehicle concepts in order to provide highly automated or even autonomous vehicle prototypes.

However, the current European Regulatory Framework does not permit the deployment of highly automated and autonomous cars because its regulations are not totally adapted to the new technologies and functionalities that are being introduced in their new prototypes. Differently from other regions in the world, in Europe vehicles must fulfill a list of particular regulations depending on their category before being commercialized. Through type-approving a particular vehicle, its safety and reliability are ensured.

In particular, regulations are being created and modified following a specific procedure in the discussion groups of the United Nations European Commission for Europe (UNECE), in Geneva, and the European Commission (EC), in Brussels.

Discussion groups

Discussion groups are groups of representatives from the Member States and experts from organizations and stakeholders. They meet periodically and when a specific subject needs more focus, smaller or specific groups are created in order to deal with it during a specific period of time. Several groups have been discussing autonomous driving, agreements on vehicle characteristics and rules for road traffic. Some are regulatory groups which are continuously improving their agreements, while others are discussion groups looking for the implementation of new technologies in the official rules.

Although both organizations, UNECE and EC, have a similar procedure of regulatory making, their structure and methodology strategies differ.

UNECE - Geneva: At the UNECE, the Transport Division holds the Inland Transport Committee which is in charge of road, rail and river transport. The Inland Transport Committee is organized in subsidiary bodies known as Working Parties (WP). Each WP deals with a specific subject; e.g. WP.1 is the Global Forum for Road Traffic and WP.29 is the World Forum for Harmonization of Vehicle Regulations. This last one is working on the adaptation and/or creation of regulations in order to enable the introduction of innovative technologies in the vehicle. The main goal is to make vehicles safer and more environmentally sound. Figure 1 below shows the structure of the UNECE.

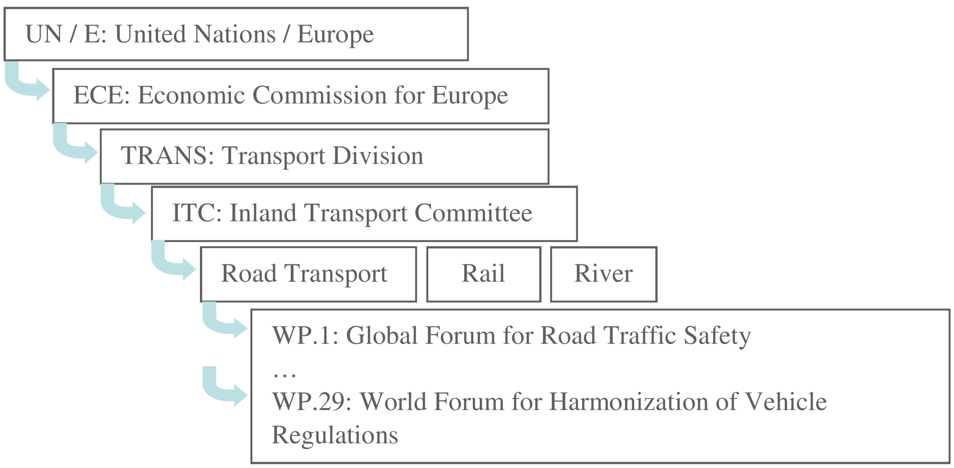

Figure 1. UNECE structure

European Commission – Brussels: In April 2016, 28 EU transport ministers signed the Declaration of Amsterdam, where all parties agreed the next necessary steps for the development of self-driving technologies. In the Amsterdam Declaration it is acknowledged that connected and automated vehicle technologies offer great potential to improve road safety, traffic flows and the overall efficiency and environmental performance of the transport system [1].

In this Declaration, actions needed to be done by the EU are outlined and described. These actions are grouped into four main pillars and are identified as follows:

- Development of a shared European strategy on connected and automated driving while strengthening the links between existing platforms such as the Cooperative Intelligent Transport Systems Platform (C-ITS), Gear 2030 and the Round Table on Connected and Automated Driving
- Continuation of the C-ITS platform for the deployment of interoperable C-ITS in the EU
- Review of the EU regulatory framework to support the development and use of automated and connected driving
- Development of a coordinated approach towards research and innovation activities in the field of connected and automated driving. As an example, at the Digital Day in Rome on March 2017, European countries signed a Letter of Intent to further intensify their cooperation on cross-border testing of automated road transport. Such cross-border tests will notably build on pilot projects funded under Horizon 2020

Cooperative Intelligent Transport Systems (C-ITS) Platform, created in early 2014, is a group that involves national authorities, C-ITS stakeholders and the Commission. Its objective was to develop a shared vision on the interoperable deployment of cooperative ITS in the EU. C-ITS allows road users and traffic managers to share information, "communicating" between them, and use it to coordinate their actions. In addition to what drivers can immediately see around them, and what vehicle sensors can detect, all parts of the transport system are thus able to share information.

The outcome of the C-ITS feeds the discussions held in the GEAR 2030 High level group on highly-automated vehicles. This high-level group was launched on January 2016 by the European Commission to ensure a coordinated approach and to address the challenges faced by the European automotive industry.

Its purpose is to build political support in order to help the automotive industry to quickly adapt to challenges from globalization, changing mobility patterns, digitalization, and environmental expectations, gathering industry and NGOs (CEOs level) and policy makers (Ministers and relevant Commissioners). Their work focuses on the adaptation of the value chain to new global challenges, automated and connected vehicles, and international harmonization and global competitiveness.

One of the most important actions taken by the GEAR 2030 group is the revision of the current legislation to enable autonomous driving. One of the conclusions of its final report submitted at the end of 2017 [2] was the revision by the Member States of their national traffic rules systems and the reporting in order to support converging approaches across the EU. Also, in this report, it was concluded that all Member States should confirm in the UNECE that the 1949 Geneva Convention and the 1968 Vienna Convention on Road Traffic were compatible with the safe use of automated vehicles with a driver expected by 2020 (level 3 and 4).

More recently, at the end of 2018, the Commission (in particular DG JRC and DG GROW) held the 1st Technical Workshop on new approaches for AD vehicle certification. The objective was to join Industry, Technical Services and Approval Authorities, so as to define a common strategy for the Safety Assessment of Automated Vehicles. The definition of this strategy will be continued in its 2nd workshop on March 2019.

UPCOMING CHALLENGES FOR REGULATORY BODIES

Historically, the UNECE Agreement on 1958, concerning the Adoption of Harmonized Technical United Nations Regulations for Wheeled Vehicles, and the EU Directive 70/156/EEC on the approximation of the laws of the Member States relating to the type-approval of motor vehicles and their trailers (later derogated by the Directive 2007/46 first and Regulation (EU) 2018/858 later), set the regulatory framework and the basis for the type-approval process as it is known nowadays.

For a Technical Service, and for a homologation engineer in particular, the task of type-approving a vehicle or component has always been a clear and unambiguous activity. Nevertheless, manufacturers are including more and more advanced systems in their vehicles, sometimes out of the scope of the regulations. This leads to an increasing responsibility for the person signing a homologation because the decision to sign or not sign is not as evident as always.

From a Technical Service's point of view, a group of "Main Challenges" have been identified. These challenges are being faced by policy makers and regulatory bodies, and current discussions held in WP.29 turn around the topics presented in the sections described below.

Challenge 1 – The time scale of legislation procedure and restructuring
The groups of experts such as the GRRF have been actively working on the creation of new proposals for regulations according to the recommendations received from the ITS/AD informal group of the WP.29.

These two groups have always been working in coordination, but the introduction of new players with disruptive technologies has increased the gap between their evolutions in time. While regulatory bodies have always evolved at a constant pace, traditional manufacturers and new player technologies are increasing their complexity exponentially.

This acceleration has led to the creation of dedicated task forces and specific working groups in the UNECE WP29 structure (see Figure 2). The GRVA "Groupe Rapporteur pour Véhicules Autonomes" (*Groups of Experts on Automated Driving*) was created in June 2018, mainly focused on encompassing activities for automated, autonomous and connected vehicles. Even though there was an Informal Working Group on Intelligent Transport Systems-Automated Driving (IWG ITS/AD), the resources were not enough to respond to the current market needs. For this reason, the organization took this decision and convened its 1st meeting on September 2018. These changes, promoted by the international regulatory bodies, were clear evidence of the willingness to adapt their structure to a more appropriate one according to the current automotive sector.

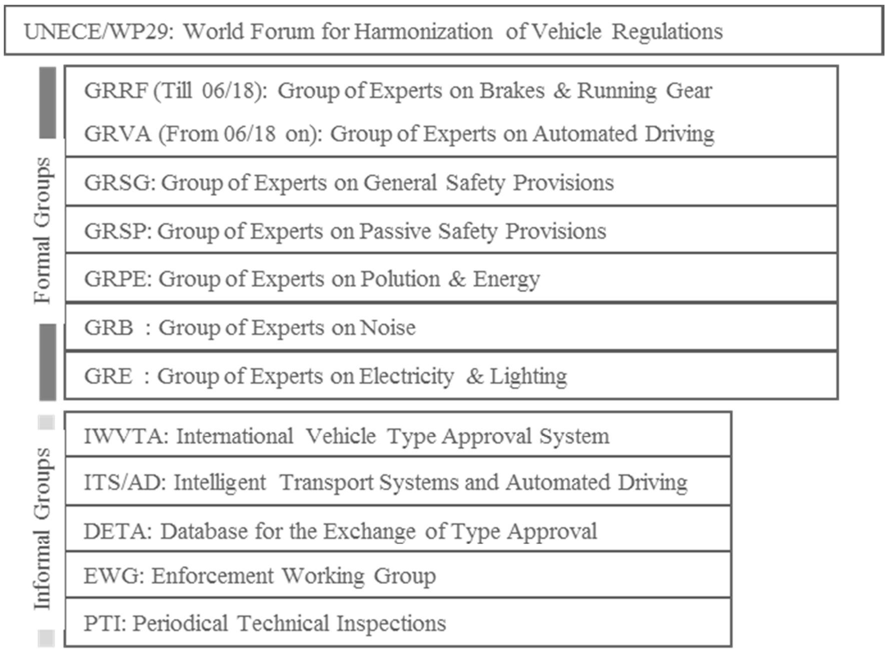

Figure 2 WP.29 Structure

For example, in order to deal with the new functionalities of the steering equipment, an informal group belonging to the GRRF was created in 2015. This informal working group was named the Automatically Commanded Steering Function (ACSF) working group.

Since its creation, the UN Regulation No. 79, dedicated to steering equipment, has been amended several times. In October 2017, the 2nd series of amendments came into force. This series brought new regulation concepts such as the division of automatically commanded steering functions into categories (A, B1, B2, C, D and E), depending on their level automatization and/or the introduction of the Corrective Steering Function (CSF). As the 2nd series only regulated the functions of category A and B1, the policy makers started working on new amendments. For this reason, a new series of amendments came out in 2018. The 3rd series of amendments will entry into force in new type approvals on 1st September 2019, bringing into place legislation functions of category C, a specific CEL in Annex 6 and the introduction of the Emergency Steering Function (ESF). Figure 3 below shows the main introductions of each series of amendments.

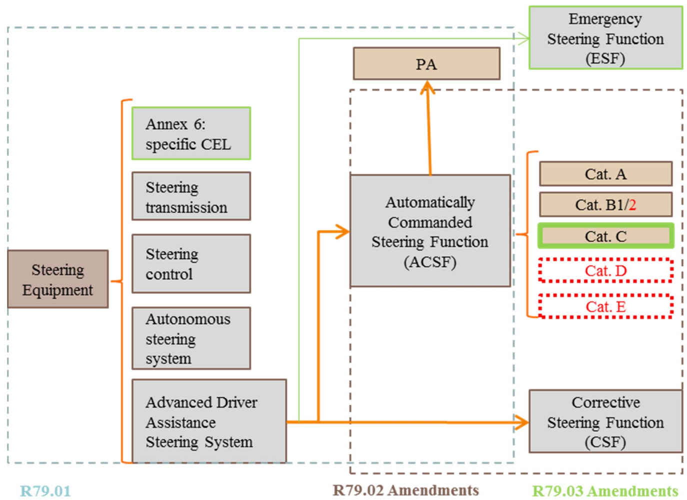

Figure 3 Series of amendments of UN Regulation 79

In last ACSF meeting, held in January 2019 in Hanghzhou [3], a proposal for Technical Requirements for an Automated Lane Keeping System was submitted. This new regulation should address the technical requirements for SAE Level 3 vehicles. According to the National Highway Traffic Safety Administration (NHTSA), SAE level 3 represents Conditional Automation, which means that the driver is a necessity, but is not required to monitor the environment. The driver must always be ready to take control of the vehicle with notice [4].

Challenge 2 – Time scale of the type-approval process

The current type-approval process consists of several predefined and standardized steps where the length of these steps is well known. Depending on the manufacturer and the workload of the technical services, this duration might change but, in the long term, it can be considered a steady process. This means that if the manufacturer is planning a new model release, the homologation process is a phase of about 6 months and they can schedule it in their plan.

This traditional process is divided into five primary phases or steps: technical documentation receipt, definition of the worst case to be tested, prototype receipt, tests performance and report drafting to get the certificate from the ministry.

However, with the upcoming change of paradigm, more stages will be incorporated to the type-approval process including new phases and aspects such as ISO 26262 for functional safety of electrical or electronic systems, Cyber-Security and Over the Air updates monitoring, simulations, among others. The introduction of more phases will increase the whole duration of the process.

This process will be reduced once the process is optimized (ISO 26262 for instance, could be shared between models) so some stages could be shared for the same manufacturer.

Determining how long the whole process is going to take is still unknown. That is why, it is important for manufacturers to consider this time factor when planning to launch their product on the market.

Challenge 3 – The role of the driver

The role of the "driver" as known nowadays is under discussion. According to the Convention on Road Traffic of Vienna of 1968 [5], the concept "driver" is defined as *any person who drives a motor vehicle or other vehicle (including a cycle), or who guides cattle, singly or in herds, or flocks, or draught, pack or saddle animals on a road.*

Nowadays, it is compulsory to get a driving license to drive a motor vehicle, which is granted by the traffic authority of each country. In the case of Europe, the driving license enables you to drive through any Member State of the European Union.

However, the upcoming change in AD vehicles is the new role of the "driver" or, preferably, the lack of it. Instead of drivers, experts are using other expressions like users or operators. So, one could think that if no one is in control of the vehicle, there is no need to own a driving license to use it. But, somehow, it must be ensured that the vehicle fulfils the road traffic rules and understands the signals or daily life events on the road such as road works, heavy rain, the approach to a flock of sheep, etc.

Experts are considering new ways to ensure that the vehicle fulfils and understands the general traffic laws. This consideration or proposals are further detailed in the chapter *Considerations and proposals to certificate the vehicles of the future* (page 8).

Challenge 4 – The gap between technology and legislation

The current applicable Directive 2007/46/EC [6] includes an article that specifies the requirements for type-approval exemptions; *Article nº 20 Exemptions for new technologies or new concept,* where Member States may, on application by the manufacturer, grant an EC type-approval in respect of a type of system, component or separate technical unit that incorporates technologies or concepts which are incompatible with one or more regulatory acts listed in Part I of Annex IV of the mentioned Directive.

This means that if a manufacturer has a model which does not fulfil one of the regulations necessary to grant a type approval, they can use this Article 20 as an alternative.

Member States may issue a temporary approval valid only in its territory, providing the following information to the Commission and other states:

- The reasons why the technologies or concepts in question make the system incompatible with the requirements
- A description of the safety and environmental considerations concerned, and the measures taken
- A description of the tests, including their results, demonstrating that, by comparison with the requirements from which exemption is sought, at least an equivalent level of safety and environmental protection is ensured

Published on May 2018, the new Regulation (EU) 2018/858 [7], has adopted this article in Article 39 and it will enter into force on 2021.

However, the forthcoming vehicle technologies cannot be considered as exemptions themselves, regulations will have to evolve in order to overcome their actual limitations.

Challenge 5 – Societal acceptance of the "unknown" level of risk

The number of accidents in developed countries has been decreasing in recent years. According to the Eurostat, there were 50 road traffic victims in total per million inhabitants in the EU Members [8].

The defenders of AD vehicle deployment argue that the introduction of AD vehicles in the vehicle park will lead to a reduction of traffic fatalities. The even more optimistic claim is that it is the only plausible strategy to get to zero traffic fatalities.

Although the long-term benefits of AD are unquestionable and probably true, experience has shown that it is not plausible to prevent accidents during the implementation process. For this reason, even if the final objective is to get zero fatalities, the way to achieve this goal is not clear. It depends on the society and institutions to declare the number of fatalities that can be accepted and in which period. The level of exigency of society will impose the complexity or number of regulations regarding AD legislation.

If the authorities decide to accept a temporary increase in road fatalities before achieving the turning point; they will also have to establish a limit in terms of time and number of accidents/fatalities.

Challenge 6 – Change of paradigm in passive safety
One of the remarkable changes that will be introduced is the concept of "living mode". This new method of transport will replace the existing "transport mode" by creating new experiences while being in a vehicle.

Using the phone, sleeping or even writing emails while going to work or on holiday will be a reality in the near future. But, even if road fatalities are supposed to tend to zero, the safety of vehicle users cannot be decreased. This means that manufacturers will have to include new passive safety systems. Airbags, seat belts, head supports, etc. will have to be redesigned and redefined.

In addition, it will be necessary to do new research into human injuries in case of accident. The main reason is that passengers will be able to "sit" in new positions adopting postures that could lead to more harmful injuries if an accident occurs.

In parallel, other systems such as lighting and signalling will need to be adapted. The International Automotive Lighting and Light Signalling Expert Group, named GTB, presented in the las GRE meeting the signalling requirements for automated and autonomous. Their objective is to take this opportunity to consider a global solution, instead of letting national authorities reach their own conclusions. For this reason, in last GRE they proposed to create a Special Interest Group to deal with this in conjunction with other stakeholders.

Challenge 7 – Dealing with disruptive transitions
A key factor to guarantee the success of the deployment of AD vehicles in the current traffic network is the management of the transition period. AD vehicles, standard cars, buses, trucks, pedestrians and other multiple vehicles and modes of transport will cohabit on the roads.

Although this transition will wake up public opinion and generate controversy, this is not the first transition seen in the cities. Not so many years ago, people experienced the transition from horses to cars. The late 19th and early 20th centuries were actually the age of streetcars. In the US, for example, the first cars appeared between 1920 and 1939 and their presence increased very fast leading to changes in the transport infrastructure and network.

However, is it possible to predict how many years take to replace the worldwide car fleet? In 2016, there were around 88 million passenger cars and light commercial vehicles sold worldwide, according to the study "National car data" presented by Macquarie Research in January 2017 [9]. According to the automotive trade journal Ward's Auto, it is estimated that by 2035 a record of 2 billion cars will be beaten. Considering these two factors, it can be easily estimated that it would take, at least, 23 years to fully replace the car fleet, considering only passenger car and light commercial vehicles.

This means that, even if the trends are met and there is not any unexpected event, AD vehicles will have to live together with all other transport modes without causing a catastrophe.

Challenge 8 – User awareness of new technologies
Linked to the societal acceptance of AD vehicles, another challenge for AD manufacturers are societal awareness of the technology.

Even if new generations (known as Gen Z, iGen or Centennials) are very used to disruptive technologies, AD vehicles are supposed to be available to everyone. This means that it is necessary to make sure that all drivers, the new ones and the existing ones, understand well all functionalities.

In addition, it is not enough to ensure that the user knows what a particular functionality does. It is important to make sure that this person clearly knows the limits of the system and he/she is aware of his/her responsibilities. For instance, if someone is using a functionality of SAE 3, that can be activated or deactivated, it must be clear when the vehicle must be under the control of the driver and who is the ultimately responsible in each mode of use.

A misuse caused by misunderstandings or unawareness of the technologies used in the roads can easily lead to accidents and fatalities that must be avoided.

Challenge 9 – Cyber-security and planned obsolescence
It is widely held that certain gadgets, cars and other devices have deliberately short lifespans. This is known as planned obsolescence. In smartphones, for example, the software updates are usually only available for the latest versions, which force the user to buy a new model of smartphone. As a result, manufacturers can sell more units and increase their sales. This situation could be transposed to vehicles. Instead of having a car that can run for more than 30 years, new vehicles could include systems that become obsolete after a limited period or use.

On the other hand, cyber-security is an issue that highly concerns the international regulatory bodies. Today, cybersecurity is present in everyone's life. In the automotive sector, as ADAS depends on an array of electronics, sensors, etc., these systems could lead to safety risks to passengers and other pedestrians if a minimum high standard of security and safety is not guaranteed.

Since December 2016, a new Task Force on Cyber Security and Over The Air issues was created. At the end of 2018, the Test Phase for draft UN Regulation on Cyber Security and Software Updates was presented. The aim of this "test phase" is to provide some guidelines on how to assess the regulatory requirements and verify the effectiveness of the regulation while verifying at the same time that Approval Authorities and Technical Service are able to reach the same conclusions based on identical OEM documentation [10].

Challenge 10 – Adaptation of the vehicle life cycle
Considering the standard cycle of a vehicle in Europe, this is basically divided into the following phases: initial assessment, homologation and authorization, Conformity of Production (COP), in-use compliance and Product Technical Inspection (PTI). With the new Regulation (EU) 2018/858 [7] new priority focus has been pointed out: Market Surveillance (MS) and Continuous Technical Inspection (CTI).

Since September 2015, when the Diesel gate scandal came out, market surveillance has become essential to avoid more cases like this one.

Furthermore, the fact that software updates and communications between the vehicle and other agents (V2X, V2V, V2I) will probably be over the air, approval authorities and policy experts consider it is important to have a CTI to authorize manufacturers to modify the vehicle software after approval.

CONSIDERATIONS AND PROPOSALS TO APPROVE THE VEHICLES OF THE FUTURE

Nowadays, five approaches are being considered to face the future of the homologation process. These five proposals are:

1. Classic homologation: Where a limited number of relevant test cases are selected, respecting the criteria of representativeness, repeatability and statistical relevance. These tests are supposed to be performed in proving grounds at the Technical Services, and according to all the vehicle regulations.

2. Real-world test drive: In this case, two different approaches can be chosen; through mileage validation or through the "digital driving license" concept. On the one hand, the mileage validation process is based on the idea that the vehicle is considered approved if it drives "X" kilometres without accidents. On the other hand, the digital driving license is based on the concept that the vehicle should be approved if it is able to pass a certain circuit that is representative of the real world. While the first process' limitation is clearly its expensiveness in terms of time and costs, the drawback of the second option is the difficulty of choosing a relevant representative circuit for the vehicle.

3. Simulation: This method enables to virtually test a very extensive list of test cases in a short period of time. Although programming the scenarios can be very expensive in terms of time and costs, once they are created the exploitation of the scenarios will help reduce time and cost validation.

4. Audit – Process oriented: The audit can be at three different levels: organizational, quality and assessment. The first one, the organizational audit, ensures that the vehicle manufacturer developing team is organized according to functional safety standards. The second one, the quality audit, guarantees that the AD function that is being validated has been developed according to ISO 26262, which sets the functional safety standards minimizing the safety risks due to malfunction of the vehicle hardware/software functions. The third one, the assessment, guarantees that the functional safety has been correctly considered in the function development.
5. Manufacturer declaration: Last but not least is to trust the vehicle manufacturer by means of a "manufacturer declaration" or "self-certification". This way to proceed is the one used in some countries such as the US to certify the vehicles sold in their country.

According to the International Organization of Motor Vehicle Manufacturer (OICA) [11] , automated and autonomous vehicles will need to follow a "Multi-Pillar" certification approach. Due to the difference in the scenario probability of occurrence in real-world traffic, an assessment considering only one approach (for instance Real World Test Drive) would imply to test the "typical" traffic scenarios. Thus, more critical scenarios would not be tested. Each approach has pros and cons and, probably, there is not a correct unique solution, but a combination of all the previous.

CONCLUSIONS

Until 2018, the homologation process has been clear and unambiguous. Signature decision was a consequence of an objective procedure. But, from now on, with the deployment of AD vehicles, their technologies and the huge number of functionalities and scenarios to be tested make the traditional validation process unaffordable in cost and time.

For this reason, five approaches will have to be considered all together: classic homologation, real-world test drive, simulation, manufacturer declaration and audit. In combination or not, the decision of how AD vehicles will be approved will be crucial for the proper deployment of these vehicles.

In overall terms, AD vehicles will bring a change of paradigm with lots of new challenges that all players (rule-makers, approval authorities, Technical Services, manufacturers and users) will have to solve in cooperation. Rule-makers will have to establish clear and objective procedures and prescription to avoid grounds of flexible interpretation. Approval authorities will have to define clear and harmonized designation rules and homologation processes, including COP and audit requirements. Technical Services must be technically competent and strictly follow rules and procedures. Manufacturers will have to present their prototypes, solutions and information in a way compatible with homologation. And users, even if for the moment they are not playing an active role, will have to cooperate to guarantee that the technology is not misused.

It seems that first steps have already been done to coordinate all players and come out with results in the near future. The reorganization of the WP.29 creating the GRVA working group on AD and the release of the new Regulation (EU) 2018/858 on Type Approval are clear examples of the efforts that international bodies are making to promote the proper deployment of automated driving vehicles on the roads worldwide.

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ESTIMATING EXPECTED LEVELS OF MUTUAL INTERFERENCE IN AUTOMOTIVE RADAR AND SIMULATING SYSTEM IMPACTS

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Paper Number 19-0081

ABSTRACT

The primary goal of this paper is estimate the power, due to other radar transmitters, expected to be incident on the receiving antenna of a given automotive radar, and secondly, simulate the impact this may have on the performance of an example radar system. The approach uses stochastic geometric methods to weigh the spatial, temporal, and spectral overlap, for realistic scenarios with multiple radars operating in proximity. The results show that a given radar receiving antenna may face more interference power (10 to 50 dB) than what is expected from the reference target used to specify system performance. Under these conditions, a radar system, without interference mitigation strategies, will likely suffer significant degradation in performance.

INTRODUCTION

The automotive industry is undergoing a fundamental transformation, made possible by a multitude of advancements in electronic, communication, and remote sensing technologies. Automobiles are being developed with varied levels of autonomy to increase efficiency, reduce congestion, improve safety, and provide reliable transportation to communities that formerly would be dependent on others for assistance.

This paper provides simplified expressions to estimate the environment in which automotive radars must operate, as market penetration of radar-equipped vehicles grows. Systems that operate well in environments with few other radars may suffer significant degradation of performance in radar congested environments. The results show that levels of interference based on operation of current systems in congested environments will be significant. In scenarios with many vehicles operating radars in the 76-81 GHz band, the power from other radars will likely exceed the power of echoes from targets needed for specified performance by several orders of magnitude, based on the model in this paper.

The modeling and simulation work focus on two questions:

- How much power does a given radar receive from other radar transmitters?
- How may this impact the performance of a collision warning system?

The first question is addressed by developing a model for nominal automotive radars and computing the amount of power overlapping in space, time, and spectrum. This work is done theoretically, assuming free space propagation of RF waves.

The second question is addressed by introducing the power computed for the interference, as noise, into a system simulation. This approach is common in past studies, and assumes the waveforms of the interfering radar are substantially different, so that their mutual energy does not correlate. This approach is taken here, in part, because it requires a minimum of assumptions about the signal processing chain behind the receiving radar's front end. To quantify possible system impacts, the processing functions are based on a generic model developed in cooperation with industry professionals and simulated in MATLAB's Automated Driving System (ADS) Toolbox. For this reason, the approach here does not capture the system impacts which depend on the multitude of interactions possible with different waveforms.

While radar interference is a well understood phenomena and studied for many decades, the concern of when and how this will impact the development of advanced driver assist systems and autonomous vehicles is relatively new. The European funding project MOre Safety for All by Radar Interference Mitigation (MOSARIM) began in January 2010 with the main objectives:

- Investigate possible automotive radar interference mechanisms
- Assess possible countermeasure and mitigation techniques

The MOSARIM study focused on simulation and empirical measurements to identify interference levels, evaluate mitigation strategies.

As well as the MOSARIM study, many other researchers have made contributions to the study of this problem, and were consulted for this study [1]-[6]. The novelty of this research is that it represents an end-to-end estimation of mean interference power for realistic traffic scenarios, and a modification of the MATLAB ADS Toolbox to simulate the system impact.

RADAR MODEL

In order to compute the interference level for a radar, we must create a model for the system under test, as well as the interfering systems. The model must be of sufficient fidelity to estimate the amount of power incident on the receiving aperture. For the purposes of modeling and simulation, parameters for a generic long range automotive radar were established, based on values selected from radar specifications.

The power arriving at a receiving antenna, P_{Rx}, from a transmitter at a range R, is a function of the power of the transmitter, P_{Tx}, gain of the transmitting antenna, G_{Tx} the wavelength of the transmission, λ, and the gain of the receiving antenna, G_{Rx}. This is the Friis formula [7], expressed in (Equation 1).

$$P_{Rx} = \frac{P_{Tx} G_{Tx} G_{Rx} \lambda^2}{(4\pi R)^2} \qquad \text{(Equation 1)}$$

The monostatic radar range equation computes the power received by a radar co-located with a transmitter, observing energy returned by a target with radar cross section, σ. This is written out in (Equation 2).

$$P_{Rx} = P_{Tx}G_{Tx}G_{Rx}\left(\frac{\lambda}{4\pi R}\right)^2 \frac{\sigma}{4\pi R^2} \quad \text{(Equation 2)}$$

The radar range equation shows the R^4 path-loss for radar returns, as opposed to the R^2 path-loss for transmission loss from another radar..

A long range radar for automotive radar applications is typically expected to detect and track vehicles more than 100 meters ahead. Typically, the radar performance is specified against a reference target with radar cross section of 0 dBm^2 at 100 meters.

The system noise for the radar is the product of the noise factor, f_N, and the thermal noise, which is the product of the operating temperature, T, the bandwidth of the receiver, B, and Boltzmann constant, k, expressed in (Equation 3)

$$N = f_N kTB \quad \text{(Equation 3)}$$

The values used for this paper are shown in Table I. Based on the radar range equation and the values in Table 1, the SNR, expressed in (Equation 4) for the reference target per pulse is 14.1 dB. The SNR value is before pulse compression. Following pulse compression, the signal power is elevated by the time-bandwidth product. This is accounted for in our simulation by condensing the signal power into the target range bin and uniformly distributing the noise power across the range bins.

$$SNR = P_{RX}/N \quad \text{(Equation 4)}$$

Table 1.
Parameters used for a generic long range radar to model interference level

	Value	**Units**
Mean Power	1	Watts
Reference Range	100	Meters
Reference RCS	0	Decibel Meters Squared
Bandwidth	200	Mega Hertz
Range res.	0.75	Meters
Range bins	200	Unitless
Comp. Gain	23	Decibel
Carrier Frequency	76-77	Giga Hertz
Noise Factor	10	Ratio (Unitless)
Duty Factor	0.5	Ratio (Unitless)
FOV Az.	20	Degree
FOV El.	5	Degree
Antenna Gain	27	Decibel
Az. Resolution	5	Degree
Range rate limits	[-100 100]	Meters Per Second

INTERFERENCE MODEL

This section details our approach to answer "How much power does a given radar receive from other radar transmitters?"

The expected interference experienced by a given receiver requires an estimate of the probability of intercepting (POI) other vehicles' radar transmissions in spectrum, time, and space.

Assumptions must be made about how the radar carrier frequency and pulse scheduling are selected. For this paper, the probability of intercept, POI, is based on the assumption that the choice of center frequency is selected randomly, uniformly distributed, in band, and there is no synchronization between systems on other cars.

The spectral POI for a pair of radars is based on the amount of the available band they occupy, or channel fraction. That is, a 200 MHz system, operating in the 76 to 77 GHz band, has a channel fraction of 0.2. For many operational systems, the channel fraction could be an order of magnitude smaller because the instantaneous bandwidth is chosen to be relatively narrow. For a population of K radars, the spectral POI for each of the radars is, ξ_K, is shown below in (Equation 5)

$$\omega_K = 1 - \prod_{k=1}^{K-1}(1 - CF_k) \qquad \text{(Equation 5)}$$

The temporal POI for a population of K radars follows a similar derivation, but the governing parameter is the duty factor for the interfering pair, DF_1 and DF_2. . For a population of K radars, the temporal POI, τ_K, is shown below in (Equation 6).

$$\tau_K = 1 - \prod_{k=1}^{K-1}(1 - DF_k) \qquad \text{(Equation 6)}$$

The temporal spectral overlap is then simply the product of the two, as shown in (Equation 7).

$$\xi_K = \omega_K \tau_K \qquad \text{(Equation 7)}$$

Mutual interference involves multiple radars. The radar under consideration is identified as the Ego radar. To compute the interference power at the Ego radar, I_1, we follow the approach of [6], shown in (Equation 8), which requires specification of the mean interferer density, λ, the transmitter power, P_0, the temporal-spectral overlap factor for pairs of radars, ξ_2, the minimum distance away from the Ego radar, on a road with lane spacing L, which an interferer with FOV θ must be to illuminate the Ego receiver, is $\delta = L/\tan(\theta/2)$, and the frequency dependent gain term, $\gamma_1 = {G_t}^2(c/4\pi f)^2$.

$$I_1 = \xi_2 \lambda P_0 \gamma_1 (\pi - 2\ \arctan(\delta/L))/2L \qquad \text{(Equation 8)}$$

In this stochastic geometric approach, the expected interference level is integrated over the interfering radars, so the temporal-spectral overlap is taken pair-wise. An example is computed in the Results section.

System Model

To estimate the impact of interference on a collision warning system, the study introduces the interference power, calculated in the interference model (8), and introduces the interfering transmissions as uncorrelated noise. This approach is common in past studies and assumes the waveforms of the interfering radar are substantially different, so that their mutual energy does not correlate. This requires a minimum of assumptions about the signal processing chain behind the receiving radar's front end. While the approach neglects the possible impacts of interfering signals, which generate false tracks (ghost targets), the impact of elevated noise is less dependent on hardware architecture.

To quantify possible system impacts, the processing functions are based on a generic model developed in cooperation with industry professionals and simulated in MATLAB's ADS Toolbox. The approach can be adapted for higher fidelity models, with the specific signal processing chain for a particular brand and model of radar. However, in this study, the system model is intended to demonstrate the impact on a generic, but reasonable, radar system that can be reproduced by other researchers with access to the ADS Toolbox.

To model a vehicle with advanced driver assist sensors, it is necessary to be able to instantiate, manipulate, and support interactions between the various components within the scenario. This framework described here incorporates:

- Roadway definitions
- Scene actors, including pedestrians and vehicles
- Motion of actors within the scene
- Definition and placement of sensors on the vehicle(s)

- Sensor detection model
- Support for combining detections into tracks

The model must have the ability to extract per-time-step information relating to vehicle positions, detection and track information, and modify on a per-time-step basis the detector responses based on changing scene conditions.

For our simulations, we implemented the processing flow shown in Fig. 1.

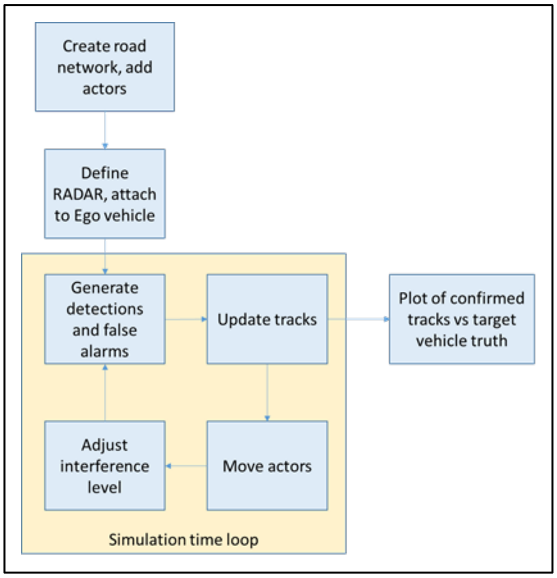

Fig. 1. Simulation Processing Flow

To implement our simulations, we chose to use the MATLAB platform (from MathWorks), with the add-on ADS Toobox. Introduced in 2017, the ADS Toolbox provided most of the capability we needed. In those instances, where it did not provide the desired interface, the implementation of the necessary extensions proved straight forward.

Generating Roadways and Vehicles

The ADS Toolbox provides methods for defining roadways, actors (vehicles and pedestrians), and motion profiles for those actors. The roadways are constructed from two-lane road segments, defined by a set of center-points in Cartesian coordinates (x, y, z) along the segment. The center-points are connected by piecewise clothoid curves.

Three classes of vehicles are referred to in this paper:

1. The Ego vehicle is the subject of interference.
2. The Target vehicles is the object, against which, the Ego vehicle's track performance is evaluated.
3. Interfering vehicles are other vehicles in the scenario with active radars.

Vehicles are added to the roadway by specifying a set of waypoints and velocities. The waypoints, like the road centers, are Cartesian coordinates. Examples of these displays are shown in Fig. 2. In this case, the Ego vehicle is blue, and the Interferers are yellow.

Sensor Definition and Placement

Sensors are attached to vehicles. Once a sensor is attached, it moves with the vehicle as it traverses the roadway. Each sensor has an update rate, which controls the number of detections the sensor generates, and may be different than the update rate of the scenario (i.e. movement of the vehicles).

The values of these parameters used in our simulations are shown in Table 1. An example display of an Ego vehicle radar azimuth field of view is shown in Fig. 3.

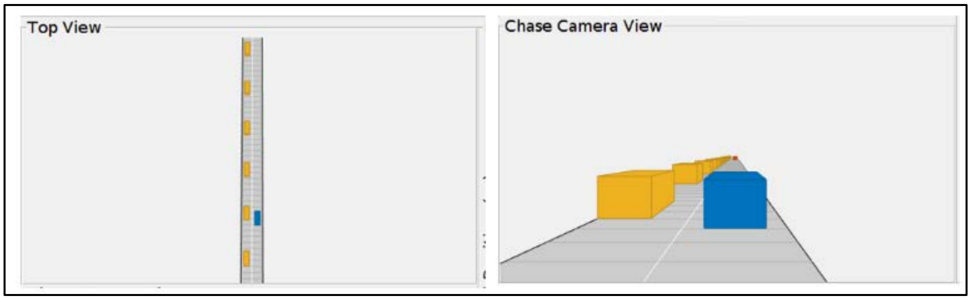

Fig. 2. Generated roadway with vehicles, where the Ego vehicle appears blue, and interferers are yellow.

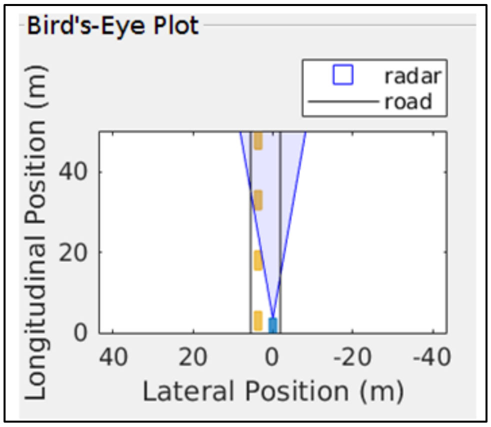

Fig. 3. Overhead view showing radar beam indicating azimuth field of view.

Modelling Detections

Detectability of targets is governed by three inter-related parameters: Probability of false alarm (PFA), probability of detection (PD), and signal-to-noise ratio (SNR). Probability of false alarm relates to the number of false detections that are allowed to occur. To insure that detections of real targets are generated, some amount of false alarms must be allowed. For our simulations, the PFA was set to 1e-6, meaning that a false alarm will occur every 1,000,000 detections. This PFA was selected to be on the low end of PFA values that are valid for Albersheim's equation (1e-7 < PFA < 1e-3), based on industry practices of limiting false alarms. The expectation is that some false alarms will be eliminated via the tracking system, since unlike true detections from vehicles, the false alarms may not correlate with a reasonable trajectory.

Once an acceptable level of false alarms has been set, the relationship between the PD and SNR is defined via a Receiver Operating Characteristic (ROC) curve. The ROC is derived from well understood radar reflection phenomenology. In the ADS Toolbox, radar reflections are assumed to be from non-fluctuating targets, with non-coherent pulse integration, generated via Albersheim's detection equation [8]. While this model for reflections is adequate for many uses, with more time and effort, this equation could be replaced with a richer model from Snidman's equations [8], based on Swerling models that provide for fluctuating responses generated from collections of potentially non-homogeneous scattering mechanisms of targets.

Detections are generated on a per-time-step basis. First, actors within the scenario are moved to their current position. Next, point targets are generated for the scene. The region-of-interest (ROI) is defined by the orientation and field-of-view of the radar. This ROI is sub-divided based on the minimum spacing defined by the azimuth and range resolutions as demonstrated in Figure 5, (in these simulations, elevation resolution is infinity, i.e. responses cannot be separated by height). Actors are represented as 6-sided cuboids. At most three sides of an actor are visible to the radar at any time. Point targets are generated wherever the side of an actor occupies one of the sub-divisions of the ROI.

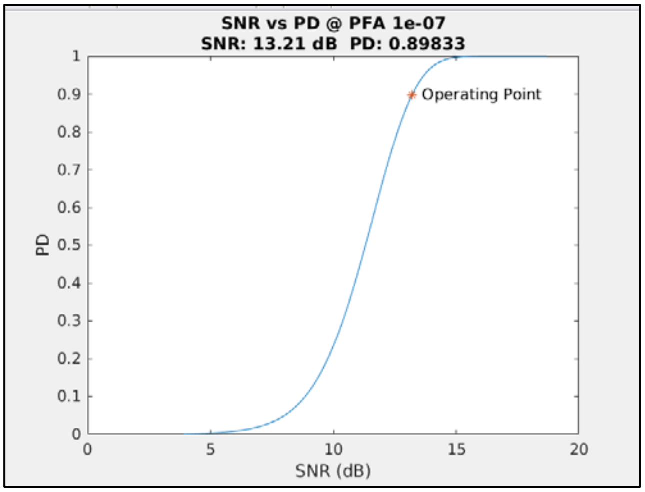

Fig. 4. Example ROC curve relating SNR and PD given desired PFA

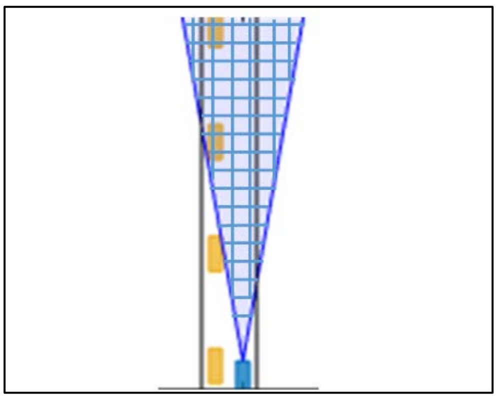

Fig. 5. Example of subdividing radar beam to identify point target responses

Each point target is assigned a radar cross section (RCS) value. This is the idealized response of the target at the given angle, without accounting for distance between the sensor and the target. Each actor is assigned a set of RCS values, which can differ with illumination angle. These set of RCS values are interpolated to get the point target response given the per-time-step illumination angle of the target. For our simulations, all vehicles are assigned an RCS value of 10 dBsm for all angles, which has been found in previous work [8] to be a good estimate of vehicle cross-section.

Point targets are then eliminated based on range rate. Range rate is a measure of the radar's ability to discern changes in relative range between the Ego and target vehicles. The limit on this ability comes from the rate at which the radar can transmit pulses, driven by an engineering tradeoff between expected maximum vehicle velocities, maximum range extent, and cost of the radar system. Point targets outside the minimum/maximum range rate are considered spurious and ignored.

Since the RCS of the target does not account for the distance between the sensor and point target, this number must be converted into the SNR at the point target. The SNR for each point target, SNR_T, is adjusted by the product of two ratios, the target RCS to reference RCS, and the two-way propagation loss (R^{-4}), at the target's range relative to the reference range, shown in (Equation 9).

$$SNR_T = SNR_R(RCS_T/RCS_R)(Rng_T/Rng_R)^{-4} \quad \text{(Equation 9)}$$

The total number of false alarms generated are chosen by calculating the total number of resolution cells for one sweep of the radar and multiplying that number by the false alarm rate. If false alarms are generated, the range and azimuth locations of the false alarms are chosen at random from a uniform distribution. False alarms are assumed to be marginal detections, therefore the SNR of each false alarm is set by applying Albersheim's equation, from [8], at the detection threshold level. Finally, the false alarms are grouped together with the target detections into one set of radar detections.

The radar detections are then fed into a tracking algorithm in order to attempt to group the current detections with previous detections and tracks. Any current detections that cannot be assigned to previous tracks are used to create new tracks. Previous tracks that are assigned new detections are updated and confirmed. Any tracks that did not get a new detection are initially coasted and, if they continue to fail to obtain detections in the future, are eventually deleted. The default tracker used in the ADS Toolbox, and in this paper, is a constant velocity linear Kalman filter.

The main metric used in determining the ability of the radar to detect a target in the presence of interference and noise is the terminal track range. This is the maximum range of a continuous track of the target. In other words, this is how far out the radar was able to initially detect the target and maintain that track through the completion of the simulation.

EXAMPLE SCENARIO

Consider a two lane highway with interference caused by forward looking radars on cars travelling opposite directions, as shown in Figure 6, below. The interference is measured at the Ego vehicle, shown in blue. The source of the interference is the radars on the yellow cars, *interfering vehicles*, travelling in the opposite direction. The impact of the interference on the system will be evaluated by how well the Ego vehicle can detect and track the green car, the Target vehicle.

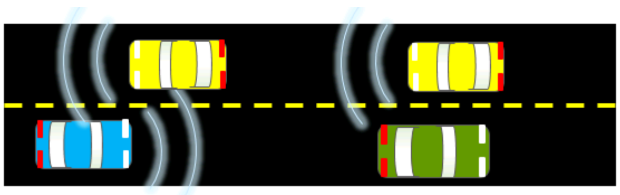

Fig. 6. Example scenario is represented schematically above. The Ego vehicle, in blue, operates a forward looking radar, following a target vehicle, in green. The Ego vehicle suffers from the interference of radars on the yellow cars travelling in the opposite direction.

The Ego vehicle is travelling at 80 kilometers per hour, and the Target vehicle is 200 meters ahead, travelling at a speed of 20 kilometers per hour. The two vehicles will collide after 12 seconds. The Interfering vehicles are Poisson distributed in the opposing lane with mean separation of 15 meters. The lane spacing is set at 3.7 meters, which is a nominal center to center spacing of US road ways.

RESULTS

The interference can be computed as a function of the density of the opposing traffic, by substituting in the values for all the other parameters determined by the lane spacing and radar parameters. Replacing the variables in (4) with the values that follow: $\xi_2 = 0.1$, $P_0 = 1\,W$, $\gamma_1 = 2.794 \times 10^{-2}\,m^2$, $\delta = 20.98\,m$, and $L = 3.7\,m$, we have an expression for the interference power at the Ego radar, I_1, as a function of the mean spacing of interfering vehicles, $\bar{x}$, in the opposing lane, in (Equation 10).

$$I_1(\bar{x} = \lambda^{-1}) = 1.32 \times 10^{-4}\,(W\,m)/\bar{x} \qquad \text{(Equation 10)}$$

For this situation the interference power is inversely related to the spacing of the interfering vehicles. If the mean spacing between the vehicles in the opposing lane is 15 meters, the interference power in (5) is estimated to be -51 dBW. For convenience, we assume the radar pair use significantly different waveforms, and following pulse compression, the power is uniformly spread over the 200 range bins. Thus, each range bin suffers approximately -73 dBW of interference power. The reference target is a 0 dBsm target at 100 meters, which using the same radar parameters has a return power of -107 dBW in the range bin at 100 meters.

The impact on performance is shown graphically, for the simulated system, by observing the distance from the target at which a *terminal* track is formed. A terminal track implies that the same track is maintained until the time of collision. Without interference, a terminal track is formed for the Target vehicle at a range of 196 meters, plotted in Fig.7. With interference, a terminal track with the Target vehicle does not exist beyond 21 meters, plotted in Fig.8. In both cases, additional tracks form as the Target vehicle becomes resolved in azimuth.

The implication is, without significant interference mitigation, the example automotive radar system, will suffer significant loss of performance for ADAS applications, as the range to the target is only 11% of the reference target specification. However, it should be stressed that this example is intended to high-light the approach on a generic radar model.

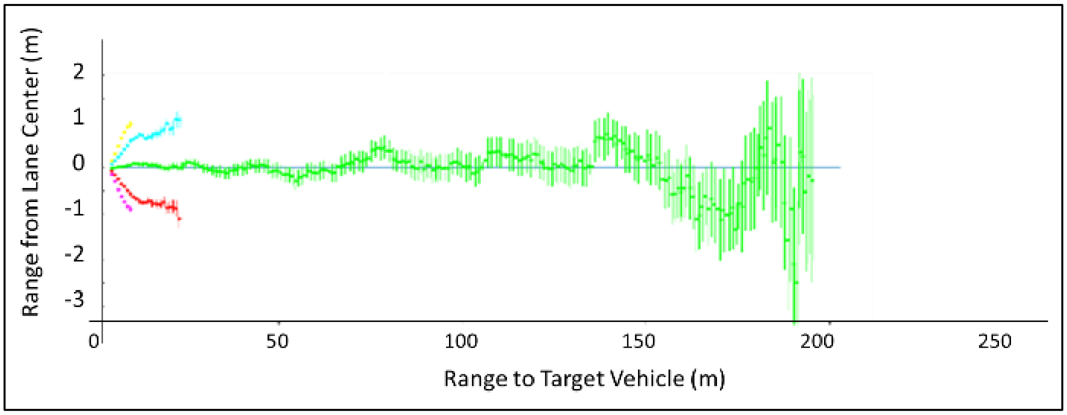

Fig. 7. Plot of terminal target tracks from example scenario, long-range radar with no interference. The plot shows the track position and uncertainty plotted as range from the Ego vehicle to the Target vehicle.

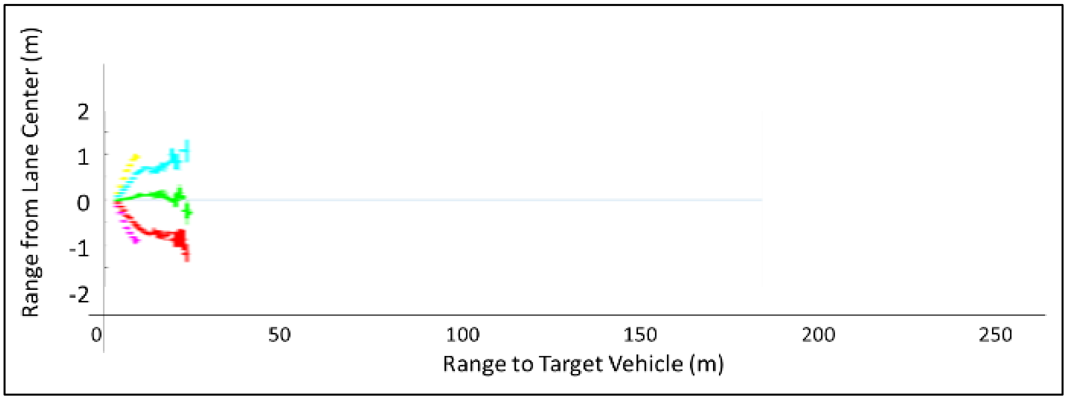

Fig. 8. Plot of persistent target tracks from Scenario 1, long-range radar, with interference, for the case of 76-77 GHz band. The plot shows the track position and uncertainty plotted as range from the Ego vehicle to the Target vehicle.

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INTENTION OF MANOEUVRE AND MOTION PREDICTION OF OTHER ROAD USERS: A HYBRID APPROACH

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Paper Number 19-0023

ABSTRACT

Automated driving is gaining more and more interest in the recent years. In order to drive safely, automated vehicles reconstruct the environment using mainly the information coming from the in-car sensors. By using this reconstruction a prediction of the future states of the surrounding vehicles can be computed, which in turn is used to decide which manoeuvre and accompanying path to accomplish. This problem is known as motion prediction. Whilst physics-based models perform well on a short horizon, machine learning has the potential to predict a more accurate motion on a longer horizon, especially if the manoeuvre of the other road user is known in advance (manoeuvre-based prediction).

In this paper a hybrid approach is proposed that consists of an intention of manoeuvre predictor, a physics-based motion predictor and a manoeuvre-based motion predictor.

The vehicles around the host vehicle are continuously tracked. The intention of manoeuvre predictor, based on Support vector machines (SVM), computes the probability for each surrounding vehicle of changing lane or of staying in lane. In addition, a kinematical model which assumes a constant turn rate and velocity (CTRV) is used to predict the trajectories. Once the intention of manoeuvre is known, the manoeuvre-based motion model, based on machine learning algorithms as Gaussian Processes and SVR, predicts the lane change or lane following trajectories. The models are trained using a collection of cut-ins manoeuvres from 60 hours of naturalistic driving. In the end, the physics-based and the manoeuvre-based motion predictions are merged together by a weighting function.

The models were validated with cross-validation and the performance and the integration between sub-modules was tested in a Hardware In the Loop (HIL) environment. The models are capable of detecting the intention of a surrounding vehicle of changing lane with a positive predictive value of 82% 1.2 second before it crosses the lane marker. The combination of SVR and CTRV is capable of predicting well for shorter and longer horizons, keeping the advantages of both methods. The combined model predicts the longitudinal distance and the lateral distance with an error that is 50% lower than the one using the physics-based model, after 4s and an even better performance on shorter horizons in comparison with SVR.

The presented approach is capable of predicting the motion of the other road users in a standard situation. In order to handle more sophisticated scenarios, the road information should be used for training. The training set needs to be extended for better results and the models need to be validated on safety-critical scenarios.

A hybrid approach for predicting the motion of vehicles from a host vehicle perspective is presented in this work. A combination of machine learning and physics-based models is used to enhance the accuracy of the prediction in shorter and longer horizons. The information coming from the prediction module can be used path planning of (partly) automated vehicles.

The results and the integration in the HIL environment show great potential to allow autonomous driving to go to higher levels of automation.

INTRODUCTION

Automated driving is gaining more and more interest in the recent years. In order to ensure more safety on the road, higher levels of automation are needed. The automated vehicle must be able to reconstruct the environment using the information coming from the in-car sensor. The current state of the environment and traffic around is not enough to make safe decisions on which path to follow: prediction of the future states of road participants around the automated vehicle is required.

Another important use case in which the prediction of other road users is needed is truck platooning, when two or three trucks drive with short inter-vehicle distance to reduce fuel consumption and improve traffic efficiency [1]. Early prediction of the behaviour of the car performing the cut-in will help to increase operational safety, because the controllers can use this additional information to anticipate the behaviour of the car, which is especially important in case the Vehicle-To-Vehicle communication fails.

The prediction of road participants can be separated in two phases: intention of manoeuvre and motion prediction. The intention of manoeuvre prediction gives as output the most likely manoeuvre that the road participant will accomplish, before the manoeuvre has clearly started. Typical manoeuvres are lane change, lane following, accelerating, braking, turning. The intention can be predicted using e.g. logistic regression [5] or Support Vector Machine [6].

The motion prediction gives as output the most likely trajectory that the road participant will follow in the future. Machine learning is broadly used to accomplish this task, for example using Gaussian Processes [7], Gaussian Mixture Models [8], Bayesian Networks [9], Neural Networks [6], Support Vector regression [4].

Based on [3], there are 3 main families of motion prediction algorithms:

1. Physics-based models: kinematics or vehicle dynamics is used to predict the motion in the future.
2. Manoeuvre-based models: the intended manoeuvre is known and based on this, the motion is predicted.
3. Interaction-aware models: the motion is modelled taking into account the interaction with the other road users

Interaction-aware models will be not considered in this paper, because they require a big amount of data in order to be trained. The focus of this work is predicting the intention and the motion of other road users on the highway, where the complexity is still limited and interactions can be ignored up to a certain extent. In this case, manoeuvre-based approaches can achieve a good performance ([10], [12]), if the intention of manoeuvre is known in advance.

Whilst physics-based models perform well on a short horizon, machine learning has the potential to predict a more accurate motion on a longer horizon, especially if trained on a manoeuvre-specific training set. In order to get the best out of both methods, physics-based prediction and machine learning can be combined. For example in [11] Dynamic Bayesian Network and Constant Turn Rate and Acceleration (CTRA) are used to predict lane change motion.

In this paper a hybrid approach is proposed that consists of an intention of manoeuvre prediction, a physics-based motion predictor and a manoeuvre-based motion predictor.

The models are then integrated in a Hardware In the Loop (HIL) environment and are suitable for online deployment in an automated vehicle.

METHOD

The objective is to increase safety of automated vehicle by making predictions of the future states of road users on the highway, catching the intention before the manoeuvre actually started, from the point of view of the instrumented vehicle (host vehicle).

In order to predict the motion of other road users, we segmented our solution into the following modules:

- Intention of manoeuvre predictor
- Physics-based motion predictor
- Manoeuvre-based motion predictor
- Combination of the physics-based and manoeuvre-based models

The general architecture of the abovementioned modules is depicted in Figure 1. The intention of manoeuvre predictor computes the probability for each surrounding vehicle of cutting in or of staying in lane. In addition, a kinematical model is used to predict the trajectories (short term). Once the intention of manoeuvre is known, a manoeuvre-based motion model, predicts the cut-in trajectories (long term). In the end, the physics-based and the manoeuvre-based motion predictions are merged together by a weighting function.

In the next subsections, the different modules will be explained in detail.

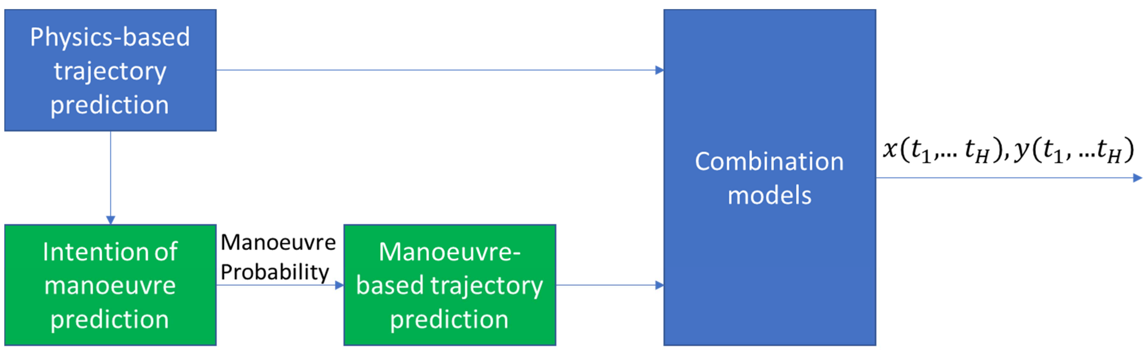

Figure 1 High-level architecture of the prediction models. The green modules are data-driven, based on machine learning. The blue modules are based on physical laws and rules.

Intention of manoeuvre prediction

The manoeuvre intention predictor, based on Support vector machines (SVM), computes the probability for each surrounding vehicle of cutting in or of staying in lane. The vehicles around the host vehicle are continuously tracked. To achieve the most accurate input for the cut in manoeuvre intention prediction algorithm, tests are performed with a high accuracy measurement system (OxTS) together with the vehicle sensors (radar and MobilEye camera). In total 80 cut-ins are performed in a highway setting. The data of all these cut-ins are synchronized at the moment of lane crossing. The start of the cut-in is defined as the last time when it a velocity towards the lane marker (looking back from the moment of lane crossing). As a control, lane keeping data is gathered from naturalistic driving. From all this data relevant parameters are extracted:

- Lateral distance/velocity and acceleration (to vehicle and lane)
- Longitudinal distance, velocity
- Yaw angle, rate and acceleration

These parameters are used in a SVM machine learning algorithm to classify an upcoming cut-in. The final chosen parameters are based on a performance check based on cross validation and a sequential forward selection method where additional parameters need to contribute at least 5% to the performance score to be included. Furthermore a simple computation provides the time it will take to this cut-in to provide an indication of the algorithms usefulness. Finally a validation is performed on said naturalistic driving data to provide an insight in the algorithms accuracy. In this validation a cut-in is predicted when the probability is higher than 0.95 for at least 0.1s to prevent unstable predictions.

Kinematic motion prediction model

For the kinematic model a constant turn rate (w) and velocity (v) algorithm is used (CTRV) [2]. This algorithm computes the longitudinal (x) and lateral (y) position and yaw angle(α) over a certain prediction horizon vector (T) as shown in the equation below:

$$x(T) = \frac{v}{w}\, sin(wT)$$

$$y(T) = \frac{v}{w}\, [cos(wT) + 1]$$

$$\alpha(T) = wT$$

where $T = [t_1, t_2 .. t_H]$.

Manoeuvre-based motion prediction model

Once the intention of manoeuvre is known, the manoeuvre-based motion model, based on machine learning algorithms, predicts the cut-in trajectories.

The machine learning models used are Gaussian Processes and Support Vector Regression. In general Support vector Machines and Gaussian Processes are capable of predicting only one value in the future. To make them predict a complete trajectory, an architecture called Direct Recurrent was used, as explained in our previous work [7]. This allows to avoid the propagation of error typical of recurrent architectures but to keep the relationship between consequent timesteps. The two models will be called DR-SVR and DR-GPR from now on.

The resulting predicted trajectory will be a couple of positions over time, with a horizon t_H up to 4 seconds:

$$(x(T), y(T)) \ = ((x(t_1), y(t_1)), (x(t_2), y(t_2)), \dots (x(t_H), y(t_H))$$

with $t_H = 4s$.

The prediction algorithms were developed by training on vehicle-kinematics data of cut-ins. The selected features are:

- Host vehicle: speed and acceleration.
- Other road user (to be predicted): longitudinal speed and acceleration, longitudinal and lateral distance with respect to host vehicle.

The training set was extracted from naturalistic driving data, that is part of the TNO Streetwise scenario database [13]. The vehicle used was the a passenger car with a radar and Mobileye system for lane detection**.**

Combination-hybrid model

Based on the crossvalidation results, a weighting function was designed to combine the outputs of the two models (see Figure 2). The physics-based model is used for a horizon up to 1.6s, afterwards only the manoeuvre-based is used. In the first interval of time a combination of the two is output, starting with 100% of physics-based output going to 100% of manoeuvre-based output after 1.6s. The cut-off value 1.6s is the horizon at which the manoeuvre-based model starts to perform better than the physics-based one when predicting the longitudinal distance, as it will be presented later in the Result section.

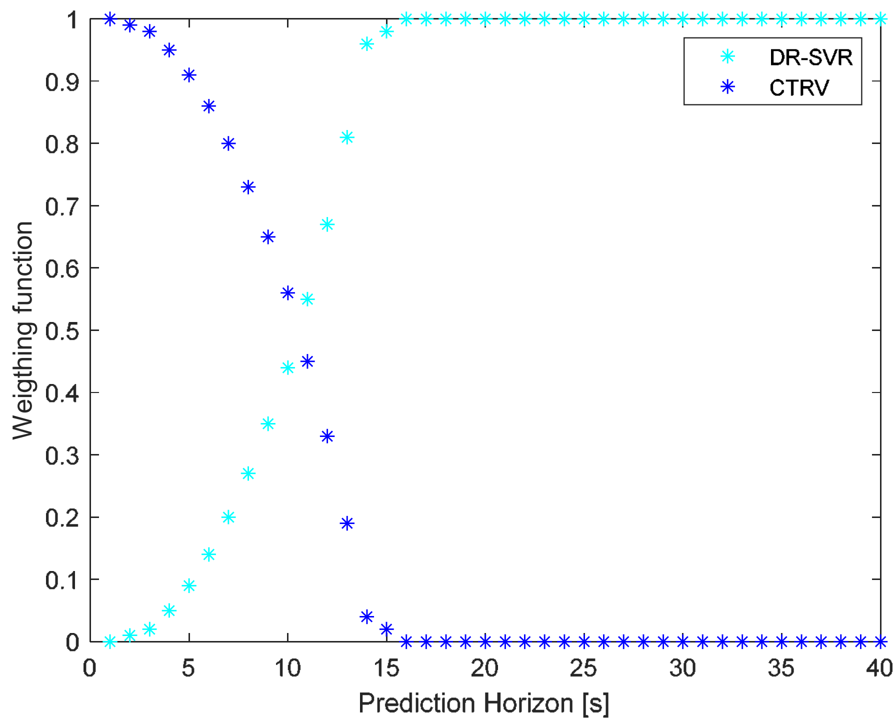

Figure 2 Weighting function used to combine the physics-based model (CTRV), in blue, and the manoeuvre-based model (DR-SVR).

RESULTS

Intention of manoeuvre prediction

For the intention of manoeuvre prediction algorithm the distance to the lane marker had the highest predictive score. Adding the velocity towards the lane made the prediction even better. Adding the best parameter in the third round (longitudinal distance) only added ~2% in prediction score. For that reason this and all following parameters are not included. Figure 3 shows the data used for the cut-in prediction with the cut-in (blue) and going straight events (black) with respect to the selected parameters. It can be seen that cut-ins can be identified by a small distance and substantial negative velocity to the lane marker. The outcome of the SVM machine learning algorithm can be seen in Figure 4. From this result a probability of an cut-in can be computed by using the current values of the 2 selected parameters.

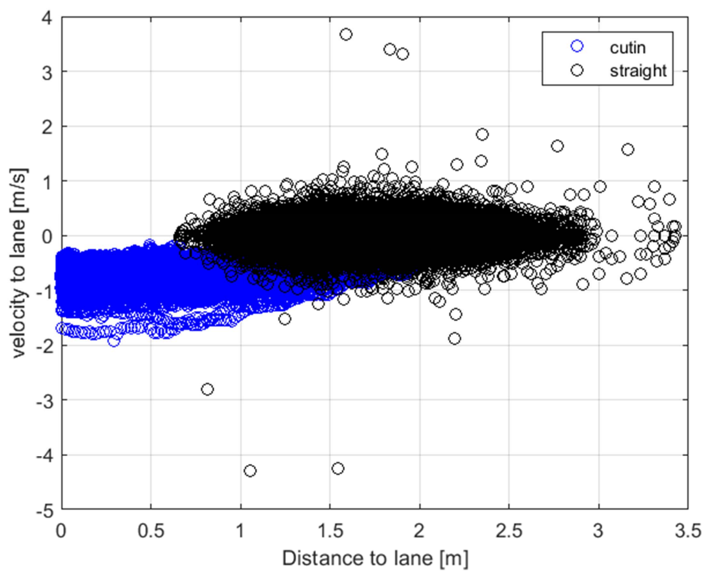

Figure 3 Data used to make the prediction algorihm with the selected parameters on the x- and y axis. Blue is cutin data and black is lane keeping data.

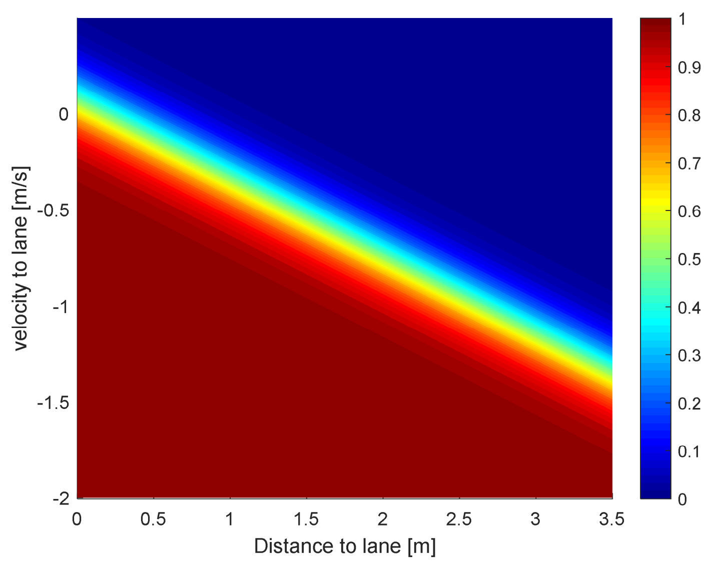

Figure 4 The cut-in prediction algorithm based on distance and velocity to the lane marker. Red area is high chance on a cut-in, while blue are is low chance

The validation showed a positive predictive value of 82%, meaning that 82% of a positive detection are cut-ins. At the moment of detection the average time to lane crossing for these cut-ins is 1.18s (0.27 STD).

Manoeuvre-based prediction

For the manoeuvre-based prediction, two models were considered: DR-SVR and DR-GPR models, as explained in the section Method. The models were validated with cross-validation and the root mean square error for the longitudinal distance and lateral distance are depicted in Figure 5 and Figure 6 respectively. For DR-GPR, the lateral distance RMSE does not exceed 0.5m, while the longitudinal distance RMSE is within the 1.6m limit after 4s. After 1s, 2s, 3s, 4s, DR-SVR has a RMSE of:

- 0.08m, 0.28m, 0,64m and 1,15m for the longitudinal distance

- 0.22m, 0.28m, 0.30m and 0.30m for the lateral distance.

DR-SVR suffers less from the small size of the training set, showing lower errors for both distances. For this reason, we will use this as baseline for the combination with the physics-based prediction result, described in next subsection.

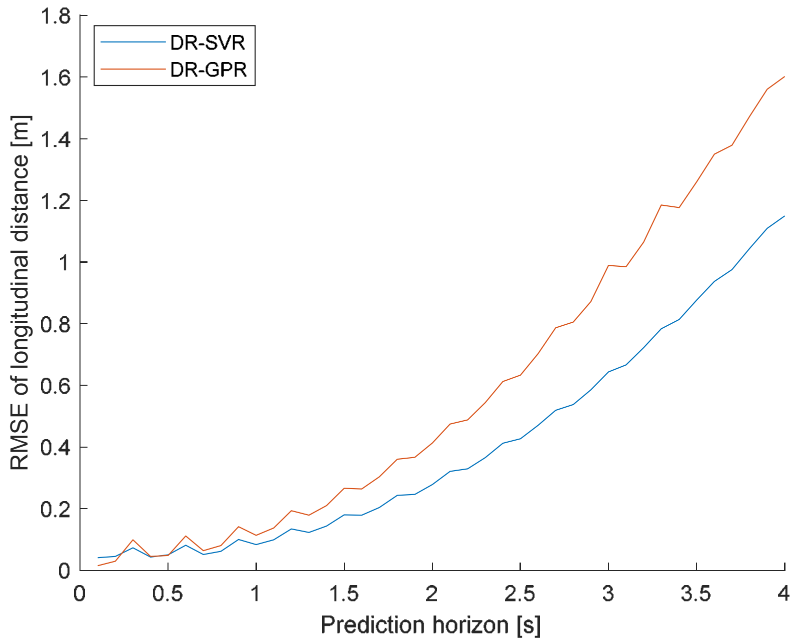

Figure 5 RMSE over time of longitudinal distance: the blue line and red line correspond respectively to DR-SVR and DR-GPR.

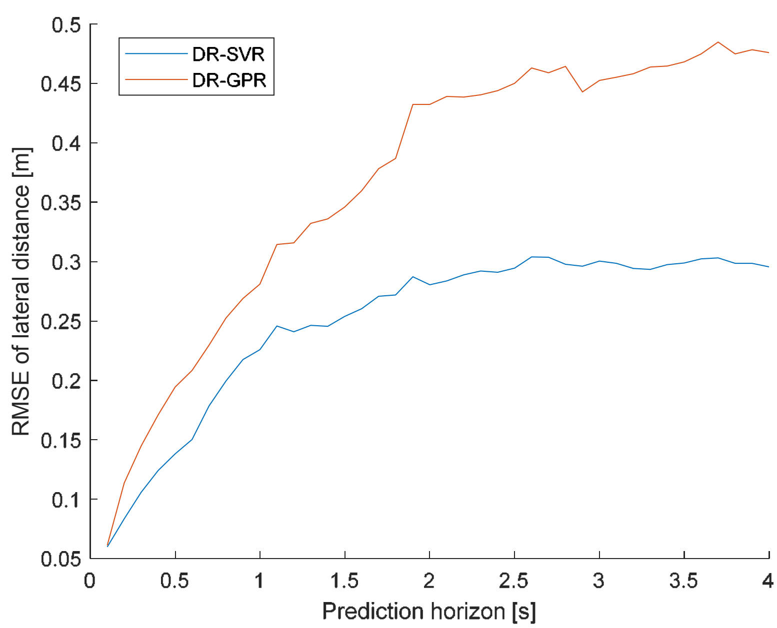

Figure 6 RMSE over time of lateral distance: the blue line and red line correspond respectively to DR-SVR and DR-GPR.

Comparison of physics-based and manoeuvre-based trajectory prediction

The manoeuvre based models (DR-SVR and DR-GPR) were compared with the physics-based (CTVR). Based on the results, the combination of DR-SVR and CTVR was based on the weighting function depicted in Figure 2.

As the CTRV requires more input signals than DR-SVR and DR-GPR in order to perform well, a new validation set was chosen to compare the performance of the different models. We selected the same set used for training the maneuver intention predictor, as explained in Method section. In Figure 10, the profiles of lateral distances of cut-ins are depicted; as it can be seen, both right and left cut-ins are included in the set.

In Figure 8 and Figure 9, the RMSE of the longitudinal distance and the lateral distance are showed. The physics-based model, CTRV, outperforms the manoeuvre based models up to $1.6s$ for the longitudinal distance and $2s$ for the lateral distance. The results show that the manoeuvre-based approach outperforms the physics-based approach for longer horizons, especially DR-SVR for longitudinal distance and DR-GPR for lateral distance. The combination of DR-SVR and CTRV is capable of predicting well for shorter and longer horizons, keeping the advantages of both methods. The combined model predicts the longitudinal distance and the lateral distance with an error that is 50% lower than the one using the physics-based model, after 4s. Looking at short horizons, the combined model is characterized by a RMSE that is one sixth of the RMSE of DR-SVR after 0.5s for the longitudinal distance and a RMSE 62% lower than DR-SVR for the lateral distance. Some examples of prediction are depicted in Figure 7.

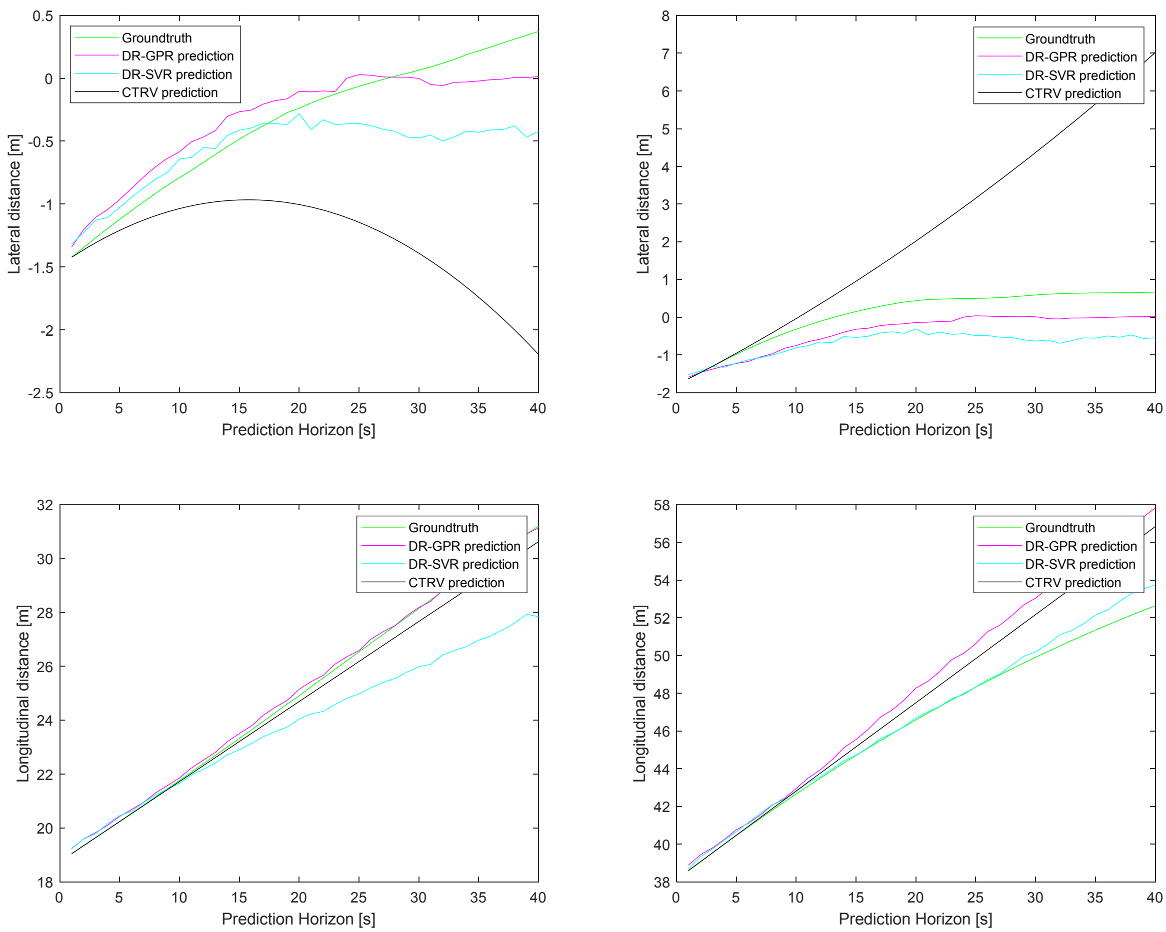

Figure 7 Examples of predictions using the different models. The groundtruth is represented in green, DR-GPR in magenta, DR-SVR in cyan and the CTRV in blue.

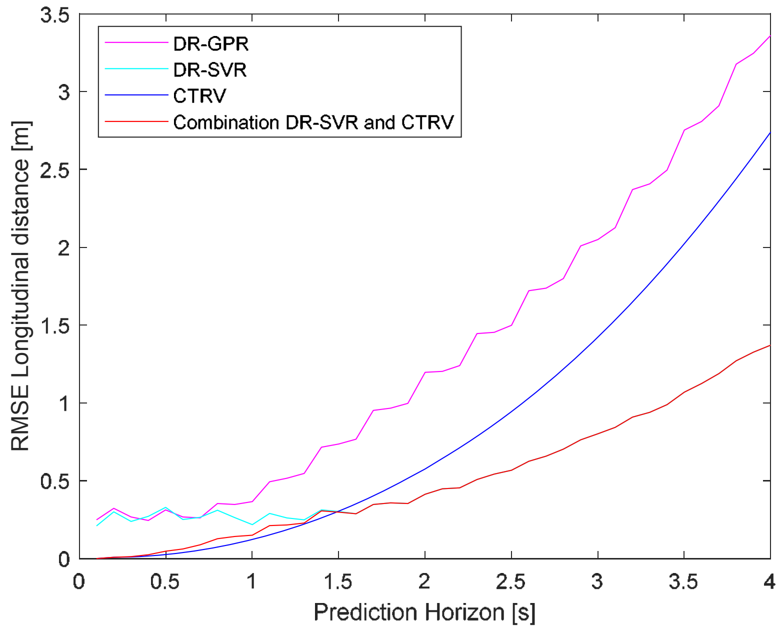

Figure 8 RMSE of longitudinal distance, based on the validation set, for the following models: DR-GPR (magenta), DR-SVR (cyan), CTRV (blue) and the combination of DR-SVR and CTRV (red).

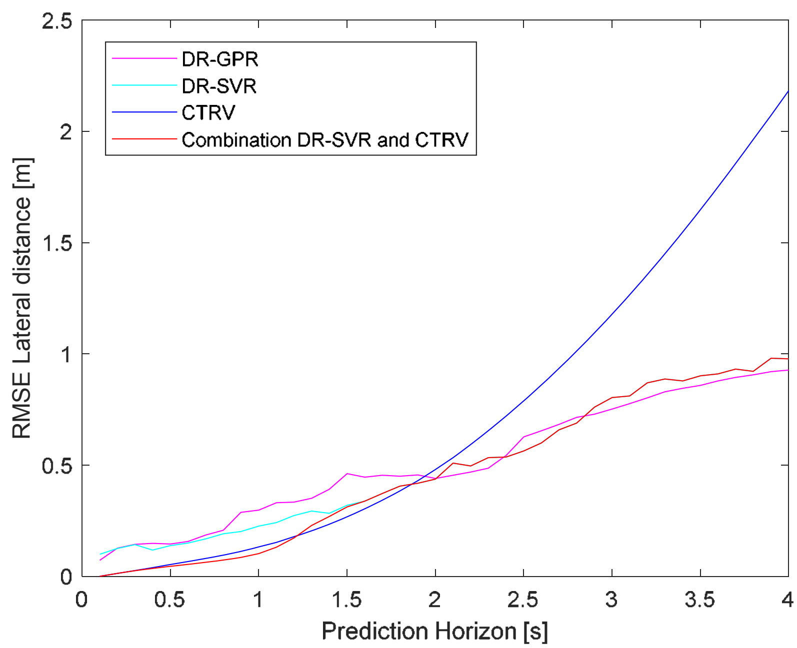

Figure 9 RMSE of lateral distance, based on the validation set, for the following models: DR-GPR (magenta), DR-SVR (cyan), CTRV (blue) and the combination of DR-SVR and CTRV (red).

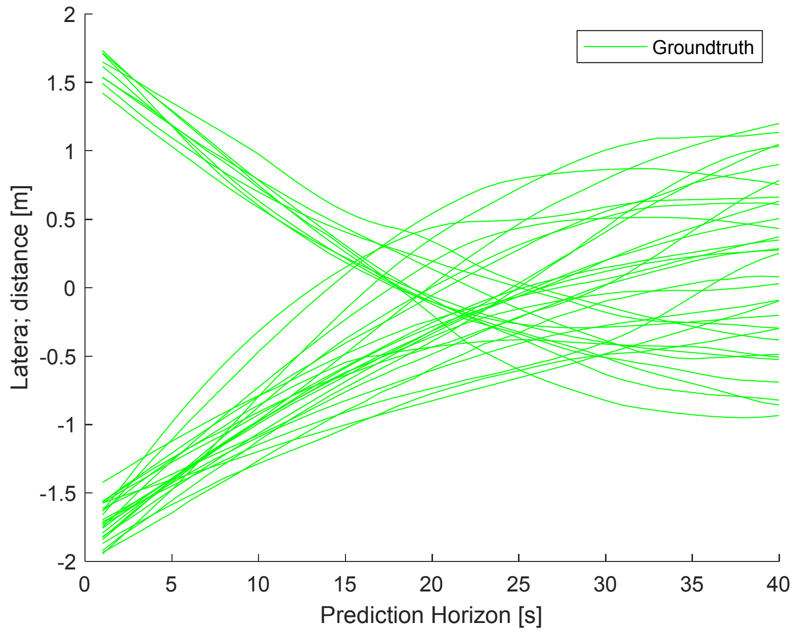

Figure 10 Validation set: the lateral distance over time of all cut-ins used for validation.

HIL setup

The prediction models are meant to be used to enhance automated driving functions. Knowing the future states of dynamic objects, as other vehicles, enables highly automated driving and increases safety. These models are often tested only via Software simulations, which can assess the accuracy of the models but doesn't ensure that these models can be integrated with the controllers and that they can infer in real-time using the data perceived by sensors such as radars or cameras. The Hardware-in-the-loop environment allows to test the functionality of the abovementioned model as if they were integrated in a real automated vehicle, testing the integration of them software and controllers with actual hardware components usually present in an automated vehicle, to give more realistic feedback. The models run in real-time and work correctly with the other components. The interfaces were facilitated by creating a ROS node of our model.

In Figure 11, three important moments from a demo video are depicted. The blue vehicle is the host vehicle, which is instrumented and it is going to predict the trajectory of the red vehicle. In the first moment, the red vehicle is not in the field of view of the blue vehicle yet. For this reason, the probability of cut-in and the time to cut-in are not measured yet. In the second snapshot, the cut-in is predicted with a probability of 98% and with a predicted time to lane crossing of 1.16s. The red continuous line is the physics-based prediction, based on CTVR. The third moment shows that the cut-in is already happening, therefore also the manoeuvre-based mode can be used, and it is the magenta line in the figure. As it can be seen, the manoeuvre-based prediction is far more accurate than the physics-based prediction.

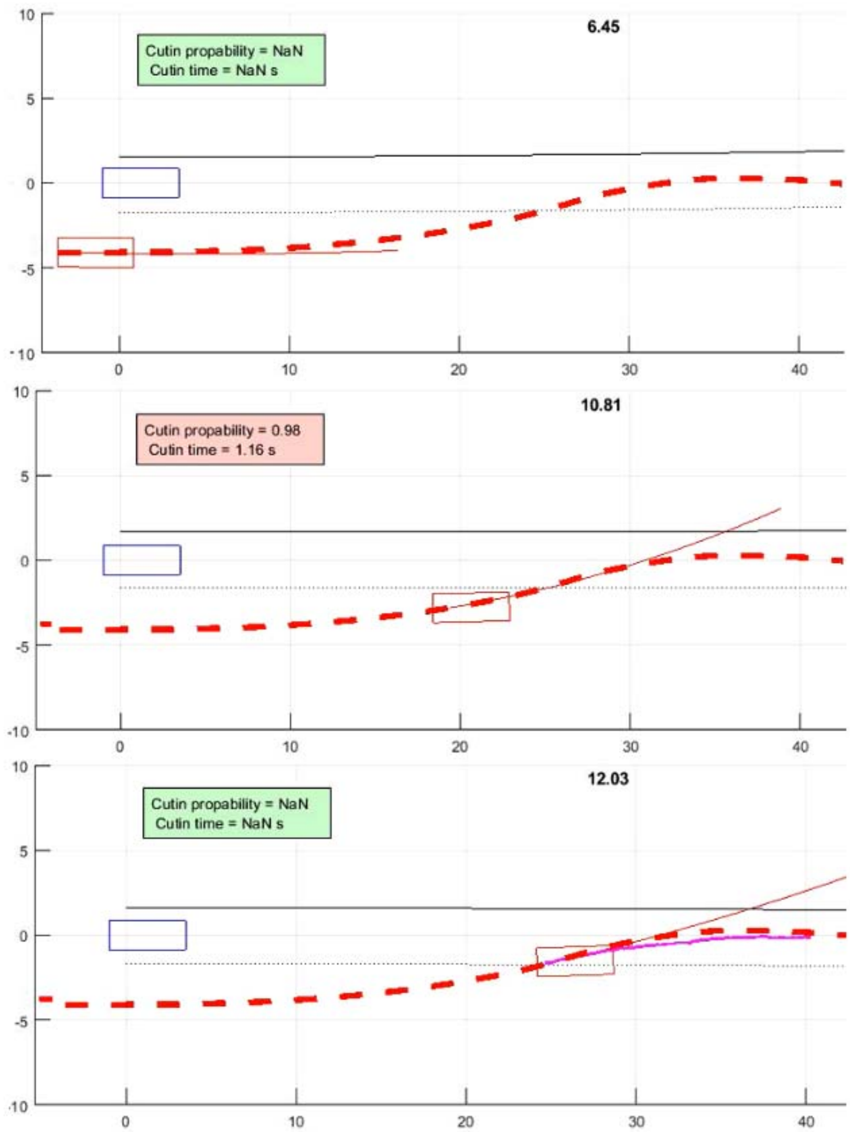

Figure 11 Three snapshots from a video where the models are functioning at the same time. The blue vehicle is the automated vehicle, which is instrumented and it is going to predict the trajectory of the red vehicle.

DISCUSSION

Validation of the cut-in prediction algorithm showed that the algorithm had problems with merging scenarios. This makes sense since the lane marker seen by the MobilEye is not the lane marker relevant for the target vehicle in merging situations. This induces large velocities towards the lane marker providing false positives. When removing these scenarios (which can be done online with the use of GPS and map data). the positive predictive value of 82% can become substantially higher when the lane detection on the Mobileye is improved. In almost all of the false positives, it is the erratic detection of the lane that triggers the cut-in prediction. For the computation of the average time to lane crossing a small portion of the detections is omitted. In this small portions the detections occur immediately when the object comes into view of the sensors, which induces a unrepresentative small time to lane crossing. In this research the Constant Turn Rate and Velocity (CTRV) kinematic model is chosen to be used for short prediction. There are other models, e.g. Constant Turn Rate and Acceleration (CTRA), Constant Steering

Angle and Velocity (CSAV) or Constant Curvature and Acceleration (CCA), which may or may not provide better results in the presented cut-in scenario.

The manoeuvre-based models have been trained also for predicting lane following trajectories and for predicting the orientation α over time. In both cases the models were not successful: the lane following set was too small to train appropriately the models, showing overfitting and therefore it was decided to use CTRV that shows quite good results for this kind of linear behaviour. Future work will focus on training machine learning models capable of predicting trajectories for lane following as well. The orientation is very difficult to predict, as it can't be accurately measured by current sensor sets and therefore the available training sets are not good enough to ensure a valid training of the models.

In the results, the Gaussian Processes model (DR-GPR) underperform compared to the support vector regression (DR-SVR), because DR-GPR suffers more of the incompleteness in the range of the feature space. However, we will keep investigating DR-GPR because of its potential. For example, it can also output the confidence of the predicted trajectory. This information is very valuable, as in case the prediction is not reliable, the automated vehicle might decide to ignore it and assume (for example) the worst case in order to ensure safety, or a set of prediction models can be used and the one with the highest confidence can be selected while driving on the road. In addition to this, gaussian processes are very good with handling noisy data, which is exactly the case for data sensed by current automotive sensor sets.

The presented approach is capable of predicting the motion of the other road users in a standard situation. In order to handle more sophisticated scenarios, the road information should be used for training. The training set needs to be extended for better results, and the validity of the models needs to be checked for safety critical scenarios. This can be done in the HIL, where critical scenarios can be simulated and therefore the models can be tested on them.

CONCLUSIONS

A hybrid approach for predicting the motion of vehicles from a host vehicle perspective is presented in this work. A combination of manoeuvre-based and physics-based models is used to enhance the accuracy of the prediction in shorter and longer horizons. The combined model predicts the longitudinal distance and the lateral distance with an error that is 50% lower than the one using the physics-based model. In addition to this, the combined model is characterized by a RMSE that is one sixth of the RMSE of SVR after 0.5s for the longitudinal distance and a RMSE 62% lower than SVR for the lateral distance. The information coming from the prediction module can be used path planning of (partly) automated vehicles. The integration in the HIL environment shows great potential to allow autonomous driving to go to higher levels of automation. Future work will focus on a broader use of machine learning for prediction and on the validation on safety-critical scenarios using the HIL environment.

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PROSPECTIVE SAFETY EFFECTIVENESS ASSESSMENT OF AUTOMATED DRIVING FUNCTIONS – FROM THE METHODS TO THE RESULTS

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Paper Number 19-0166

ABSTRACT

The development in the areas of sensors and electronics has been bringing the automotive industry increasingly closer to automated driving in recent years. Automated functions that need to be continuously supervised by the driver are already on the market. Highly automated driving functions (HAD) will enter the market in the near future. The German Ethics Commission for automated and connected driving stated in its report that "the licensing of automated functions is not justifiable unless it promises to produce at least a diminution in harm compared with human driving, in other words a positive balance of risks" [1]. This leads to the question, how the traffic safety effect of automated driving functions can be assessed taking into account possible positive and negative aspects?

This paper introduces comprehensively a method that is used by BMW for the prospective safety assessment of HAD by means of virtual experiments. This method is besides others part of the evaluation and safety assurance activities for HAD. The method is described from the scenario selection via the simulation up to the validation and verification. In contrast to other simulation approaches in this area, which mainly use accident re-simulation, this approach uses Monte-Carlo techniques, in which the initial starting conditions of the simulated driving scenario as well as the parameters of the involved drivers are randomly selected from distributions. These distributions base on accident data as well as on naturalistic driving data. A core aspect of this approach is the stochastic cognitive driver behavior model to describe the behavior of individually different traffic participants in a scenario. In contrast to accident re-simulation based approaches, this approach allows to analyze time-wise larger driving scenarios, which are of importance for HAD, since these functions act throughout the driving within the operational design domain and not only in critical situations.

The method for assessing the safety performance is applied to exemplary HAD. The results cover the positive effects, which are mainly achieved in today known accident scenarios, as well as scenarios, in which potentially new

risks compared to manual traffic can occur. One example for this is the minimum risk maneuver, for which the consequences of different implementation is discussed. Like all other methods (accident analysis, studies in driving simulator or on test track, field operational test) the simulation based approach has advantages and disadvantages. The main criticism is that the assessment is done virtual, which poses the question on the validity of the simulation. In order to tackle this aspect the validation and verification of the method and tool is a key aspect. Therefore, our current conceptual considerations regarding validation and verification are described in this paper.

INTRODUCTION

Since the 1960's different technologies have been introduced in the automobile industry in order to improve the traffic safety, see ***Figure 1***. The first type of technologies were passive safety systems (seat belt, airbag etc.). These technologies mainly aim to reduce the consequences of an accident. The next step were systems that actively try to prevent an accident or at least try to reduce – in case of unavoidable accidents – its consequences prior to the first contact. These systems are known as active safety technologies. Their development started with systems focusing mainly on the vehicle dynamics (e.g. ABS and ESC) in the 80's of the last century. From 2000 onwards further active safety systems entered the market. The systems use the information about environment and surrounding traffic in order to detect an imminent risk and to start countermeasures (e.g. AEB, blind spot detection). The third category of systems in the integrated traffic safety approach are systems that aim to prevent the occurrence of critical driving situations already beforehand. Systems of this category typically take over the control of the vehicle in longitudinal, lateral or both directions. These systems can be categorized by the SAE classification for automated driving [2]. The systems of this category range from advance driver assistance systems (ADAS), like ACC, up to highly automated driving functions (HAD). In particular the latter one is currently a major topic in the development of the automobile industry [3] [4].

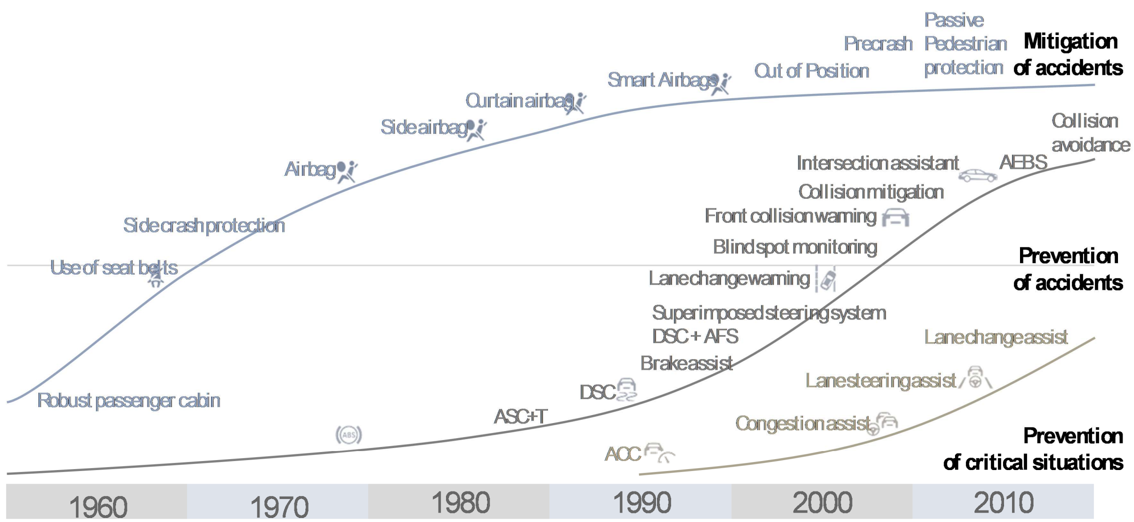

Figure 1. Integrated traffic safety approach [5].

Highly automated driving functions are expected to bring major improvements in terms of traffic safety [6] by avoiding human error related accidents. However, it must be taken into account that accidents are very rare events. Altogether 20.928 accidents occurred on a German motorway in 2017, in which a human was slightly, severely or fatally injured [7]. Considering an annual driving distance of approx. 243 billion kilometers [8] an accident with injured persons occurs statistically on a German motorway only approx. every 11.6 million kilometers. An improvement of traffic safety due to automated driving would become reality once it is proven that accident frequency is less than for human driving. Therefore, the German Ethics Commission on automated and connected driving request in article 3 "…The guiding principle is the avoidance of accidents, although technologically unavoidable residual risks do not militate against the introduction of automated driving if the balance of risks is fundamentally positive" [1]. This poses the question, how a positive balance of risk for automated driving can be

investigated and proven already before real world accident data are available. One method to investigate this balance of risk for automated driving is the prospective safety effectiveness assessment approach.
In the paper different approaches for the prospective safety effectiveness assessment are presented including BMW's simulation based approach for automated driving. This approach is later exemplarily applied for different driving scenarios. Finally, the paper ends with a description of the taken validation and verification approach for this method.

METHODS FOR PROSPECTIVE SAFETY EFFECTIVENESS ASSESSMENT

There are different approaches and tools to determine the effectiveness of a technology on traffic safety. In general the safety effectiveness assessment conducts a comparison of the situation without the technology under assessment (baseline) with the situation with the technology presented in terms of traffic safety.
At this point a distinction between the retrospective and prospective assessment approaches is necessary. The retrospective assessment is conducted after the market introduction of the technology. The assessment is typically done by means of real world accident data [9-11]. The advantage of this method is that it is capable to provide the real world impact of a technology. But there are two challenging aspects for this method. The first one is that confounding factors can hardly be controlled. The second aspect is that it requires a certain penetration rate of the technology, which means, that it cannot be used before a technology is introduced in the market or shortly after its introduction. However, the application of the method in the development is fundamental requirement, if the proof of a positive risk balance is prerequisite for the market introduction of automated driving.
The safety effectiveness assessment of the technology before its market introduction is aimed by the prospective assessment approaches. Basically, four different approaches are known. These are: field operational test (FOT), user studies in a controlled environment (driving simulator or test track), accident analysis and computer simulations. Each of these approaches has its advantages and disadvantages. The FOT approach, which has for instance applied in the euroFOT project [12], analyzes the effects of a technology in real world conditions. However, the approach requires quite high resources and can only be applied once a technology has reached maturity, which allows to test on public roads. Furthermore, due to the low likelihood of accidents, it is rather unlike that a statistical relevant number of accidents is detected in a FOT. For this reason typically surrogate measures (e.g. critical driving situations) are applied in the assessment. Studies with users on test tracks or driving simulators provide detailed information about the interaction of the user with the technology under controlled conditions and without posing the users any risk. This approach has been used in different studies, e.g. by [13]. However, these studies require also a high effort – in particular if the effect of technology should be analyzed in a large number of driving scenarios. In contrast the prospective accident analysis, which for instance has been applied in [14-16], allows to investigate the potential field of application with relative low effort. The drawback is that the approach is limited in the way, how precise the effectiveness of technology can be calculated, since specific effects in driving scenarios cannot be taken in account.
The remaining approach is the computer simulation, which has been used in different studies (e.g. [17-19]). This approach is able to investigate the safety effect of a technology in various driving scenarios at a reasonable effort. The challenging aspect for this approach is that it is done entirely virtually, which poses high requirements for the in the simulation applied models. It is also clear that input data from other tools are required to set up the simulations [20], e.g. accident data, driving simulator data, FOT data or data from naturalistic driving studies (NDS). Within the prospective safety effectiveness assessment by simulation two different approaches are known, see ***Figure 2***.

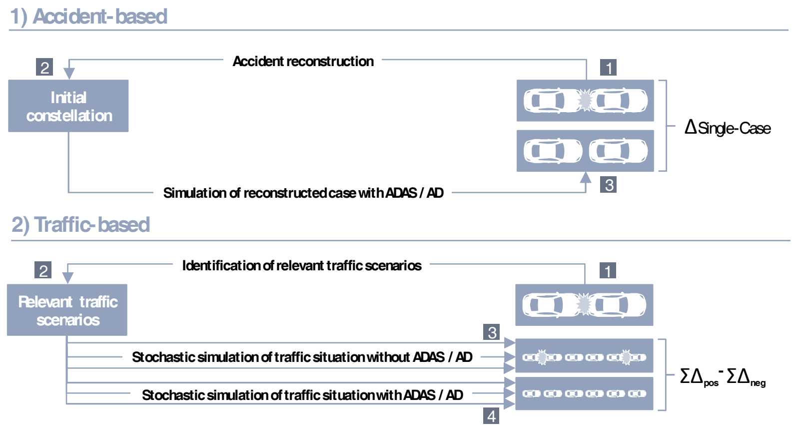

Figure 2. Approaches for the simulation based prospective safety effectiveness assessment.

The first approach is the accident-based approach. For this approach real-world accidents, which have been reconstructed, are simulated considering the technology to be assessed. The trajectory of the simulated traffic agents (combination of driver and vehicle) are derived from the original accident case. A prerequisite of this approach is that detailed reconstructed accidents are available. Examples for the application of this approach are [17] [18] [21-23]. Here, it must be noted that the uncertainty in the reconstruction increases the longer the accident case is reconstructed. Furthermore, this approach allows to investigate only critical situations. A modification of this approach in order to cover a wider range of situations can be accomplished by slightly altering the parameters of the original accident case in order to investigate, how a technology would react under the changed conditions [22] [24] [25].

The second approach is the traffic-based approach, which has been for example applied by [25-27]. Artificial driving scenarios are simulated within this approach. The starting conditions of the driving scenario are stochastically chosen from distributions that are derived from accident data or NDS/FOT data. Thus by means of the distribution the link between the simulated cases and the real world is ensured. In contrast to the accident-based approach no trajectories can be pre-calculated. Therefore, models are required that determine within the simulation the behavior of the traffic participants. For a valid simulation the quality of these models must be ensured. On the one hand there are no limitations in terms of duration and complexity (length of road, involved traffic participants, conducted maneuvers etc.) of the scenarios as for the accident-based approach. And by means of this approach also driving situations can be analyzed that are not critical in the first place, which allows to analyze, whether any false positive reactions of the technology are detected.

Due to the wide range of scenarios that can be analyzed at a reasonable effort BMW has used the traffic-based simulation approach for the prospective safety effectiveness in a wide range of different analyses [28-30] for ADAS. However, HAD poses new challenges for the prospective safety effectiveness assessment. The following sections discuss these challenges as well as the taken measures to solve them.

APPROACH FOR PROSPECTIVE SAFETY EFFECTIVENESS ASSESSMENT OF AUTOMATED DRIVING

The required adaption to apply the method of prospective safety effectiveness assessment by simulation for automated driving functions can be derived from the difference to active safety functions. First, in general each technology can have positive as well as negative effects on traffic safety. The longer the technology is operating the more situations are affected by the technology. Active safety systems, such as AEB, only operate respectively intervene in the driving dynamics once a critical situation is detected. These situations are – of course depending on the individual driving style – rare and short driving situations. In addition, the situations, in which the system is active, are clearly defined. Thus, the situation space can be narrowed down to a few types of situations. Since intervention just starts seconds before the imminent collision, the simulated time frame can rather be short. Also when assessing potential negative consequences it can be focused on situations that are short in time.

For the HAD the nature of the technology leads to different requirement. Here, the function can constantly operate through driving as long as the vehicle is in the operation design domain (ODD). This longer operation time of the HAD means that the simulation needs to cover larger and longer driving scenarios. Since during the drive different maneuvers occur, it is not enough to focus just on single maneuvers. It is rather required to simulate the entire range from normal driving via critical situations up to the moment of the collision.

Furthermore, challenging driving scenarios for HAD, which might lead to negative impacts on traffic safety, must be paid more attention compared to active safety system for two reasons. First, the longer operation of HAD and by this larger interference with the traffic raise risk of executing not for given situation appropriate actions. The second reason is that HAD leads to new driving scenarios that are not part of the manual driving today. The main example is a driving scenario in which the driver has to take over vehicle control from the function.

A last important aspect for assessment of automated driving is that the function does not only change the severity of a situation as mainly considered for active safety systems, but also can influence the frequency of certain driving scenarios. One example is the passive cut-in maneuver. First experiences on public roads already show an increase of occurrence frequency of this maneuver while driving automated compared to manual driving [30]. Since the safety effect of a technology is described by the change in the severity and the frequency in the relevant driving scenarios, such effects must also be taken into account when assessing automated driving.

These requirements lead to the conclusion for prospective safety effectiveness assessment, which is only one part of the entire test and safety assurances activities of HAD, that an assessment for automated driving is only feasible by means of the traffic-based simulation approach. The accident-based simulation approach is too limited in terms of scenario duration and selection of scenario to ensure a comprehensive assessment. Of course it must be noted that the simulation approach requires different input data. The input data must come from other sources, like accident data, driving simulator data for e.g. describing the overtaking abilities of human drivers as well as FOT and NDS data. In the following relevant aspects of the traffic-based simulation approach as it is applied at BMW are highlighted.

Analyzed scenarios for automated driving

The assessment of automated driving requires consideration of driving situations, which might lead to positive as well as to negative effects in terms of traffic safety. In order to assess these effects the relevant driving scenarios must be identified. However, as stated earlier due the constant operation of HAD driving scenario does not mean that the scenario is limited in time to a few second and to a few involved traffic participants. Driving scenario here means that a larger road section – for instance two kilometers – with depending on the pre-defined traffic flow calculated number of traffic participant is simulated in which the certain driving maneuver or a kind of conflict occurs.

BMW's approach for identifying the scenario to be analyzed bases on three pillars, see **Figure 3**. The first pillar focuses on the driving scenarios for which positive effects of the HAD are expected. These can be derived from the driving scenarios, in which human drivers do not perform well. Typically these are accident situations. The major accident types that occur on German motorways are accidents related to (passive) cut-in, rear-end conflicts at the end of traffic jams, rear-end conflicts in general and single driving accidents, in which one vehicle leave the road not directly involving any other road users.

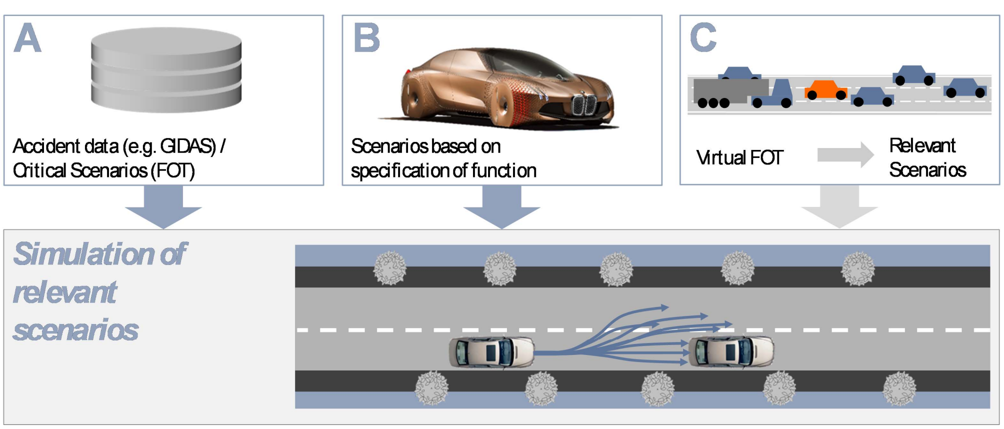

Figure 3. Identification of top scenarios for the assessment of HAD.

The second pillar considers the for the HAD challenging driving scenarios. The scenario can either have positive or negative effects. These driving scenarios are identified by means of analyzing the function itself. With respect to the accident frequency within manual driving, these scenarios are typically less relevant. Due to the uncertainty regarding the HAD behavior, they require more in-depth analysis. Examples are driving scenarios that require an interaction with other road users (e.g. highway entrance, end of driving lane), scenarios in which the HAD needs to take complex decisions (e.g. obstacle in the driving lane) and the already mentioned transition of control scenarios, in which the driver (suddenly) has to take-over the vehicle control from the function.
The last pillar addresses the issue of detecting changes in the frequency of driving scenarios. This is hardly possible by simulating driving scenarios. This requires even larger traffic simulations, in which longer and representative road sections are simulated. Therefore, BMW considers for this purpose a "virtual"-FOT approach, in which traffic scenarios with the HAD are simulated. In a second step relevant driving scenarios are identified in the output data of the simulations. This approach allows to get an understanding how the frequency of certain driving scenarios changes.

Simulation tool openPASS

Naturally, the simulation based approach for the prospective safety assessment requires a simulation tool, in which the simulation are carried out. There are several commercial tools available on the market. However, most of these tools are proprietary software tools that lead to limitations in terms of the required adaptations. Therefore, BMW does use for its approach the open source simulation tool openPASS [31], which is currently jointly developed under the eclipse foundation developed by BMW, Daimler, Volkswagen, Toyota, Bosch, TÜV Süd and ITK-Engineering.
openPASS offers the opportunity to simulate both simulation bases approaches in the prospective safety assessment, namely the accident-based and the traffic-based approaches. The modular framework of openPASS allows to include different models for the different modules, while the open source approach offers a certain transparency. Furthermore, it is possible to use within openPASS the open source interfaces such as openDRIVE, openSCENARIO, OSI and FMI. For the used approach of the HAD assessment the most important aspect of openPASS is that scenario can be simulated with several stochastic variations that could affect the environment, the vehicle, the sensors parameters and the traffic. A last important aspect is the driver behavior model that is addressed in the next section in more detail. Here, the flexibility of openPASS is used by integrating the BMW's driver behavior model in the simulation framework.

Driver Behavior Model

For the traffic-based simulation approach a driver behavior model is an essential building block. A driver behavior for the assessment of HAD is required for two purposes. The first purpose is to simulate the behavior of driver in the automated vehicle in situations, in which the driver must take over the driving task from the function. The second purpose is to describe the behavior of different traffic participants during situations considering the interaction among all relevant traffic participants. In the baseline simulation all traffic participants are controlled by the driver behavior model. In the treatment simulation the model is only relevant for the non-automated agents. Due to the fact that in the assessment a comparison between the baseline and treatment simulation is done, the risks in the baseline simulation should be comparable to the real world. Hence, the driver behavior model should cover the driving ability of a wide range of drivers including accident prevention strategies as well as faulty behavior of human drivers.
The requirement let to the development of Stochastic Cognitive Driver model (SCM) at BMW from 2014 onwards. This driver behavior model is mainly designed for highway traffic. The functional concept of the SCM combines human cognitive processes with stochastic process modeling. The SCM consists of five different sub-modules to represent the behavior of different drivers (information acquisition, mental model, decision making process, action patterns, action implementation). By means of these models it is possible to represent the process from the information acquisition up to steering, braking or acceleration actions by the agent. Due to the stochastic characteristics of the SCM it is guaranteed that agents behave differently in certain driving situations. And it is even possible that the same agent in the same situations reacts differently. By this it is ensured that a wide range of driver behavior is covered by the assessment.
Further developments of the SCM in the recent years covered two aspect. The first aspect is that the model's prediction and anticipated capabilities have been improved in order to ensure a better traffic flow and to reduce the accident rate in passive cut-in maneuvers [32]. The second aspect is the driver characteristics module. This sub-module links driver parameters (age, driven mileage) and states, such as fatigue and stress [33], with the driver parameters of the SCM. It covers individual and inter-individual driver differences and their impact on driver

behavior. In a one-way stochastic process, traffic agents are provided with a set of individual driver characteristics that shift, widen or narrow baseline distributions of stochastic parameters in all sub-modules of the SCM. By this, a broader spectrum of the over-all driver population can be modelled and virtual traffic simulations can be run as realistic as possible. For filling this sub-module with valid data, a driving simulator study has been conducted.
After the general background has been discussed, the next chapter shows exemplarily the application of the method for HAD.

APPLICATION OF METHOD FOR AUTOMATED DRIVING

After presenting the approach this chapter focuses on its exemplary application. For this purpose the effect of an exemplary HAD is analyzed in eight different driving scenarios. The eight different driving scenarios are: 1. Cut-In, 2. Traffic jam, 3. Rear-end accident, 4. Single driving accident, 5. End of Lane, 6. Obstacle in the lane, 7. Highway entrance and 8. Minimum risk maneuver after transition of control. The analysis have been conducted in the context of the European funded research project AdaptIVe [34] and the German funded research project Ko-HAF [35]. The first four scenarios are reported in the section for the accident scenarios, whereas the remaining four are reported in the section for the challenging scenarios.
It must be noted that analyzed HAD is an example function that does not represent BMW's actual implementation.

Analyzed highly automated driving function

The exemplary HAD that is simulated in the following has been implemented according to the **Table 1.** For the minimum risk maneuver that is activated in case the driver does not take over from the function two implementations are analyzed. For the first implementation a moderate deceleration (approx. 2 m/s²) and for the second implementation a strong deceleration (approx. 5 m/s²) is considered.

Table 1.
Specification of analyzed artificial automated driving function.

Category	Operation conditions
Road Type	Motorway
Conditions, when function is deactivated	Invalid environment conditions, end of motorway, defect in vehicle, loss of sensor data, loss of software module(s), construction sites
Covered environmental conditions	Dry condition and light rain in day and night
Speed range	0-130 km/h
Sensor range (front / side left / side right / rear)	200 m / 40 m / 40 m / 200 m
Covered driving maneuvers	Vehicle following in lane, obstacle or VRU on the road, lane change, stop & go driving, speed / time gap adaptation, enter and exit of motorway, minimum risk maneuver
Max. / Min. long. acceleration (normal operations)	4,0 m/s² / -4,0 m/s²
Max. / Min. lateral acceleration (normal operations)	3,0 m/s² / -3,0 m/s²

Safety performance of HAD in accident related traffic scenarios

First the driving scenarios are simulated according to the described method for which a positive effect of the HAD is expected. The change in the accident risk for the automated vehicle compared to the manual driven vehicle are given in **Table 2.** As expected all scenarios show potential to reduce the accident risk.

Table 2.
Results of the simulated accident related traffic scenarios [34].

Driving scenario	Expected mean change of accident rate [Confidence interval]	Accidents within ODD in GIDAS (including accident at speeds outside the operation conditions)
1. Cut-In	-83% [-76%; -90%]	72% (92%)

2. Traffic jam	-40% [-25%; -55%]	80% (89%)
3. Rear-end accident	-73% [-56%; -91%]	69% (96%)
4. Single driving accident	-100%* [-;-]	67% (93%)

The only scenario that has not been covered by the simulation approach is the "single driving accident". In this scenario the vehicle leaves unintendedly the lane or the road. It is expected that as long as a curve is in the ODD and no functional issues occur the function will be able to keep the vehicle in the lane and prevent by this the related accidents.
However, the effect in the driving scenario is only one part of the potential safety effect, since it implies the function can operate under all conditions and is always active. This of course does not meet the truth, since HAD is as described in Table 1 limited in terms of the ODD. In order to consider this limitation the third column in table 3 provides information about the proportion of the GIDAS accident [36] for which the ODD have been fulfilled. Regarding the proportion of the in the ODD included accident there is an uncertainty regarding accident that occur outside the operation speed of the HAD. For these cases either the function is switched on and drivers benefit as calculated or drivers intend to drive faster, which means that he/she switches the function off. This would result in no benefit at all. To a certain extent this is a country specific aspect, which is more relevant in Germany than other countries due to the in terms of speed limit unlimited German motorway. However, the principle question applies to all accidents above the operation speed of the HAD. Regarding the usage of the HAD any statement before market introduction is hardly possible, since the actual usage will depend on the HMI design and user's attitude towards the function.

Safety performance of HAD in challenging traffic scenarios

After the driving scenario with expected positive effect the challenging scenarios are evaluated. Table 3 provides the results of expected mean change of accident rate in the driving scenarios as well as the proportion of accidents in the ODD.

Table 3.
Results of the simulated challenging traffic scenarios [34][35].

Driving scenario	**Expected mean change of accident rate [Confidence interval]**	**Accidents within ODD in GIDAS (including accident at speeds outside the operation conditions)**
5. End of Lane	-14% [-8%; -20%]	67% (83%)
6. Obstacle in the lane	-40% [-34%; -47%]	78% (97%)
7. Highway entrance	-49% [-45%; -53%]	95% (95%)
8. Minimum risk maneuver (moderate deceleration)	+2.6% [+0.2%;+5.0%]	No reference data available
9. Minimum risk maneuver (strong deceleration)	+48.4% [+36.4%;+60.4%]	No reference data available

Simulations show a high variation in the results for the challenging scenarios. For obstacle in lane and highway entrance driving scenario a high potential for the reduction of accident risk is detected compared to the baseline scenario. For the minimum risk maneuver the situation differs. This does not surprise, since compared to normal driving an additional and properly for other traffic participant surprising braking maneuver is induced. For the moderate minimum risk maneuver the accident risk is approximately in the range of manual driving. The minimum risk maneuver with strong deceleration shows a significant increase of the accident risk compared to manual driving. Thus, from traffic safety perspective the deceleration in the minimum risk maneuver should be rather low. However, it is important to note in this context that the technical feasibility of applying a minimum risk maneuver has not been considered in this study. It is obvious that the implementation effort for moderate deceleration is significantly higher than for stronger deceleration, since the time that need to be covered by the maneuver is higher.

VALIDATION AND VERIFICATION PROCESS

Since the present approach for the prospective effectiveness assessment relies on virtual computer simulations, validation and verification is essential to ensure that the simulation provides trustable and reliable results. Within the validation and verification it is checked whether the results of a single model or the entire simulation meet the results of a reference within a pre-defined range. The challenge within the validation and verification for simulation is ensuring correctness of the simulation while keeping the effort for this activity at reasonable level.

Since BMW considers validation and verification as an important aspect for the method of the prospective safety effectiveness assessment, a validation and verification process has been defined for its simulation. The main requirements of BMW's validation and verification process are:

- This process must cover the entire method and all relevant (sub-)modules within the simulation method.
- The process shall be conducted at least once for each model and the entire method.
- It needs to be repeated depending on the changes on the method or on the simulation tool. For this purpose it is distinguished between minor and major changes depending on the impact of a change.
- In case already validated models are used, a further validation or verification of this model is not required.
- The reference shall be selected in accordance with to be validated model and the quality of the reference data.

An overview on models that can be validated and verified by means of different reference is given in the **Table 4.**

Independent of the taken approach, it must be decided in the end whether the output of the validated model is close enough to the reference. For the definition of the criteria the purpose of assessment as well as the quality of the reference data are of relevance. In case explicit criteria (e.g. max. error) are available, it shall be shown that these thresholds are met. This applies also if a certain target range is defined. Here, it can be necessary to break down into permitted inaccuracies per model. In case no explicit criteria is available the quality of a module can be quantified by one of the following approaches:

1) Calculation of a quality indicator (max. error).
2) Quantification of technical deviations between distributions (e.g. effect size).
3) Sensitivity analysis.
4) Explicit declaration of confidence intervals.

Table 4.
Reference data for different models in the validation and verification of simulation models.

Reference	**To be validated simulation model**
Real world effectiveness based on accident data	Entire method, collision model
FOT or NDS	Traffic module, driver behavior module
Test on test tracks	Vehicle module, technology module, driver behavior module
Driving simulator	Driver behavior module
Sensitivity analyses	Vehicle module, technology module
Review against the specification	Technology module
External database / literature	Environment module, driver behavior module, traffic module
Inspection	Collision module
Software tests incl. module, unit, integration and system tests	Simulation control

CONCLUSIONS AND DISCUSSION

This paper presented a comprehensive overview on the prospective safety assessment approach for HAD. The introduction of HAD leads to different challenges for the prospective safety assessment of this technology. In principle, different tools can be applied for the safety assessment. However, considering the advantages and disadvantages the simulation based assessment approach is the most promising approach for this purpose, since it is capable of covering a high variety of driving and traffic scenarios at reasonable effort. Nevertheless, the input of the other tools can and should be used for the correct definition of the in the simulation applied models. In this sense the simulation is a synthesis of knowledge that is gained by the assessment tools.

The key challenges of the simulation approach for the prospective safety assessment approach for HAD are besides the implementation of the function the identification of the relevant driving scenarios, the simulation tool and the driver behavior model. In the paper it has been reported how BMW addresses each of the issues.
Finally, the described method has been applied for an exemplary HAD. The results indicate that HAD can lead to a significant reduction of the accident risk in the specific scenarios within the ODD. For the challenging scenario the situation is not that clear. Here, also new risk in terms of traffic safety can occur. However, the differences in the outcome in terms of accident risk for the two minimum risk maneuvers emphasize the demand for detailed analysis considering the exact technology behavior as well as detailed simulations in this area.
The last challenge in the context is to prove that the derived results are reliable and trustable. Therefore, validation and verification of the method as well as the simulation tool including all models is essential. The paper reported on the taken validation and verification approach for the prospective safety assessment at BMW.

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TOWARDS A QUANTITATIVE "SAFETY" METRIC FOR AUTONOMOUS VEHICLES

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Paper Number 19-0012

ABSTRACT

Future mobility systems are expected to incorporate a broad range of transport modalities (passenger cars, truck platoons, etc.) at different automation levels (SAE Levels 3/4/5). During operation, automated vehicles will have to independently take safety-critical decisions (e.g., when to brake or change lanes) and estimate the impact of their behavior on the surrounding traffic, thus balancing individual and group safety. To achieve this, automated vehicles will require a quantitative metric of safety to guide their actions.

This article proposes one such metric, suitable for decision-making and autonomous navigation. The metric is meant to provide a quantification of the risk a vehicle incurs during operation by taking into account three main aspects of its operation: the probability of a hazard occurring (e.g., a rear-end collision), the potential impact of the driving conditions on the health of the vehicle's passengers were the hazard to occur, and the capability of the vehicle to avoid the hazard. The article focuses on introducing the conceptual aspects of the metric first and then presents the initial results on estimating and collision probabilities. The other two aspects will be addressed elsewhere.

INTRODUCTION

Automated vehicles (car, buses, trucks) are widely considered to be a promising solution to the road safety and congestion problems. On the one hand, such vehicles would not be subject to distractions or lapses of judgement that currently lead to the majority of road accident involving human drivers [1], thus improving road safety. On the other hand, their shorter reaction times and ability to communicate with road infrastructure would allow them to drive more efficiently on the roads, increasing road utilization and capacity, while improving traffic flow.

To realize the aforementioned benefits, automated vehicles would have to drive according to a notion of *correct behavior*[1], which presumably would maximize (or at least maintain) the safety level of all traffic participants. Trained (and experienced) human drivers are able to judge the safety of their situations and act accordingly (most of the time). This is generally done unconsciously based on implicitly learned behaviors and models of the world. Automated vehicles, on the other hand, must make explicit judgements about their safety in order to take decisions regarding their behaviors[2]. Such decisions may include when to activate automated emergency braking systems, which trajectory to follow while driving, which route to use to reach a particular location, when to allow a human driver to regain vehicle control, etc. Thus, reasoning about safety would be needed at several layers of an automated vehicle's architecture [2, 3].

Much as the notion of correct behavior (see Footnote 1), safety is also a difficult concept to define precisely, and it varies with the stake holder considering it. As summarized in the next section, safety has been addressed from at least three perspectives: traffic system safety, vehicle hazard (collision) avoidance, and vehicle certification (functional safety). Briefly, from the traffic system perspective, safety is related to understanding (and preventing) the factors that contribute to traffic crashes and injuries (e.g., vehicle technologies, infrastructure design, etc. [4, 5]); safety from the hazard avoidance perspective is related to determining thresholds on proximity metrics to trigger warning and/or collision avoidance systems (see, among

[1] *Correct behavior* is a societally-agreed concept that encompass not only normative or engineering-like goals (e.g., "follow the traffic rules") but also elements such as "use an acceptable driving style", which vary widely by country, age group, etc.

[2] Arguably, an automated vehicle could be completely controlled by machine-learning-based algorithms trained to mimic human driving behavior without explicitly reasoning about safety. Not all automated vehicles, however, would be so controlled.

many examples, [6, 7]; while safety from the certification perspective is related to developing the vehicular electronics and software at the necessary automotive safety integrity levels (ASILs) [8]. Unfortunately, none of these approaches directly provide a definition of safety that could be operationalized to reason safety as needed for autonomous vehicle operation.

This article, introduces a framework to compute one such metric. It can be thought of as an extension of existing techniques on estimation of probability of collision [9, 10] to incorporate measures of both the consequences of a potential collision and the ability of the vehicle to avoid such collision. The framework is modelled after the concepts used in the ISO 262622 standard to assigned ASIL levels, and the resulting metric can be considered as a measure of interaction severity, when applied to interactions of two vehicles.

The rest of this article is organized as follows: The framework of estimating safety is introduced next, after a brief summary of available literature on safety definitions. This is followed by a description of our initial work on estimating the probability of collision in two dimensions, one of the main three elements on our framework (the other two elements are outlined but described in detail elsewhere). Finally, the paper ends with out conclusions.

FRAMEWORK FOR SAFETY ESTIMATION

As mentioned in the introduction, the framework for safety estimation proposed here draws from concepts of safety defined by other researchers and stakeholders. To avoid confusion between the use of "safety" in the vernacular, and "safety" as a subject of study, the latter will be italicized in the sequel. Several concepts of *safety* are summarized next.

A Brief Overview of Safety in the Literature

Perhaps the most frequently recognized concept of *safety* comes from the field of traffic safety: it is the absence of road accidents that may lead to severe injury, deaths, and or property damages (see, e.g., [11]). From this perspective, *safety* cannot be directly measured[3]. The *lack of safety*, however, can be described via accident statistics, and it is know to have a large impact in terms of loss of life, livelihood, and economic output [13]. This is why its minimization is of great interest for governments and regulators. Minimizing (or, hopefully, eliminating) the *lack of safety*, however, depends not only on the actions of individual vehicles in traffic, but also on the right combination of vehicle technologies, infrastructure design, and traffic policies. Thus, the aim of traffic safety research is not to measure *safety* in order to allow vehicle automation, but rather to show whether or not the introduction of new technologies or traffic policies lead to demonstrable reductions of severe road accident statistics (see [14, 15] and the references therein).

The aim of minimizing the *lack of safety* as defined above, gave raise to a number of technologies that help vehicles avoid or minimize the effect of severe traffic conflicts, which in turn can lead to severe collisions [14]. Severe traffic conflicts can be defined as traffic interactions where two or more participants are in collision course and "too close" either in space or time [16]. Collision courses are determined using simplifying assumptions on the vehicles' behavior (e.g., constant acceleration), while proximity is measured using any number of indicators, most commonly, time to collision. Appropriate thresholds over these indicators allow for the automatic activation of a vehicle's warning and/or collision avoidance systems [6, 7]. Vehicles equipped with such technologies are assumed to be safer because they minimize the chance of occurrence and/of the effects of accidents, which is usually confirmed via testing (see, e.g., [17]). Note, however, that *safety* does not need to be (and it is not) directly defined/measured in these approaches.

A different perspective altogether on automotive safety is that of *functional safety*. This concepts, presented in detail in the ISO26262 standard [8] is related to minimizing the risk of occurrence of particular hazards due to technological failures (e.g., rear-end collision due to braking failure). To accomplish this, a vehicle's hardware (i.e., electronics) and software are developed in a way that they attain specific automotive safety integrity levels (ASILs). These, in turn, are derived by analyzing the time and possibility of the vehicle

[3]From this perspective, *safety* (i.e., the absence of loss of life under all traffic circumstances) cannot be formally proven. This is, however, a very compelling and important goal to pursue, as stated by the Vision Zero philosophy [12]

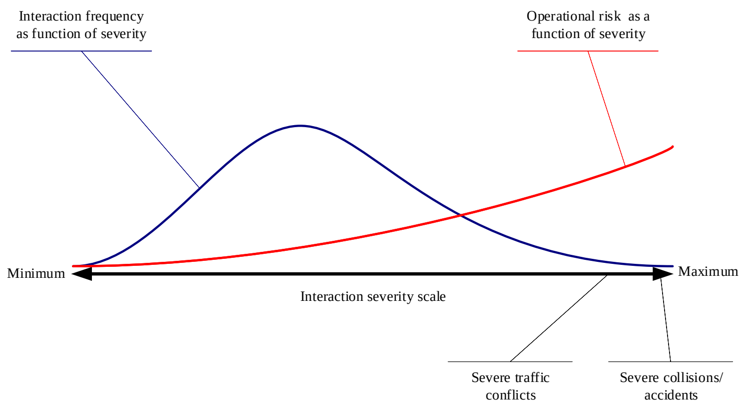

Figure 1: Severity scale for traffic interactions and associated risk (adapted from [4])

being exposed to the said hazards, the gravity of injuries that might be caused were the hazards to occur, and the likelihood that the injuries could be prevented by the actions of a typical driver. A vehicular system so designed is said to be functionally safe. Though functional safety is precisely defined in the ISO26262 standard, it cannot be directly quantified.

Finally, it is important to point out that there are several metrics in the literature that are used to allow vehicle automation [15, 18, 19]. Such metrics have been used for, among other applications, collision avoidance and path planning [6, 7, 20]). To the best of our knowledge, such metrics are application specific and do not always take into account the consequence of potential collisions on the drivers involved. The framework proposed next aims to address both these issues.

On Safety Estimation

A well-known concept from traffic safety literature is that all traffic interactions can be placed along a continuous "severity" scale [4, 14] (see Figure 1). On one end of the scale lie the least severe interactions, which lead to accidents with very low probability (e.g., a vehicle driving alone in a road). Towards the middle of the scale lie the mid-severe interactions. They are the most frequent interactions and, generally speaking, lead to accidents with low probability. On the other end of the scale one finds the most severe and rare interactions (i.e., the severe traffic conflicts) that lead to severe accidents with (presumably) high probability. This suggests that one could reason about the degree of *safety* of a given vehicle in traffic, by quantifying the severity of the traffic interactions affecting it at a given time.

Unfortunately, there seems not to be yet a consensus in the literature on how to quantify interaction severity, although it is expected that multiple indicators should be combined to produce such quantification (see, e.g., [14, 19, 21]). Here, we propose an approach motivated by the method ISO 26262 standard to assign ASILs. That is, each traffic interaction involving a vehicle of interest (called *host*) is treated as a potential hazard and assigned a severity value equal to the operational risk it imposes on the host. Clearly, the higher the severity of the interaction, the higher the risk for the host (see Figure 1).

To assign a risk value, we consider the potential hazard's likelihood, hazardousness, and avoidability[4]. The relationship among these factors are illustrated in Fogire 2: the (blue) host vehicle keeps a constant distance with the (yellow) vehicle in front of it. During this interaction, another (green) vehicle begins a cut-in maneuver between them. This maneuver creates a potential collision hazard. The risk induced by this hazard depends on the likelihood of the collision (usually estimated from prediction models). Intuitively, the higher the collision likelihood, the higher the host's risk. Further, a mild collision presents a lower risk to the passengers involved than a severe collision , as the latter has a higher chance to produce severe injuries. Thus,

[4]These concepts mirror exposure, severity and controllability in ASIL assignment [8].

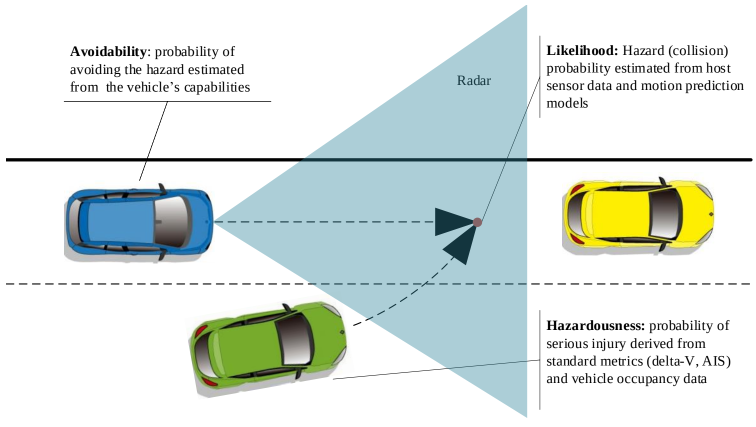

Figure 2: Example scenario showing the factors contributing to operational risk.

the hazardousness of the potential collision has also a strong bearing on the host's risk. Finally, depending on its capabilities, the host may be able to ameliorate the hazard's consequences or to avoid it all together. Thus, the hazard's avoidability also plays an important role on understanding the host's operational risk.

Formally, let $S : \mathbb{R}^+ \to [0,1]$ and $R : \mathbb{R}^+ \to [0,1]$ denote the host's (degree of) safety and operational risk functions respectively ($\mathbb{R}^+$ denotes the non-negative real numbers). Then, the host's (degree of) safety in the next $T \in \mathbb{R}^+$ seconds is given by

$$S(T) = 1 - R(T) \triangleq \mathrm{P}\{\mathcal{H}\}(1 - \mathrm{P}\{\mathcal{A}\})\mathrm{P}\{\mathcal{I}|\mathcal{H}\}, \tag{1}$$

where $\mathrm{P}\{\mathcal{H}\}$ denotes the probability that "a hazard occurs in the next T seconds" and $\mathrm{P}\{\mathcal{I}|\mathcal{H}\}$ denotes the probability that "severe injury or death occur if the hazard occurs in the next T seconds" and $\mathrm{P}\{\mathcal{A}\}$ denotes the probability that the vehicle "can perform an action to avoid the hazard in the next T seconds". These three probabilities denote, respectively, the likelihood, hazardousness and avoidability of hazard $\mathcal{H}$.

Remark 1. That a hazard occurs in a given period depends, among other factors, on the actions of the host and other traffic participants during that period. An automated vehicle can only *estimate* these future actions based on past and present sensor data and behavior prediction models. The greater the period T, the more uncertain the estimations become. This uncertainty is captured by $\mathrm{P}\{\mathcal{H}\}$. ⧫

Remark 2. $\mathrm{P}\{\mathcal{A}\}$ estimates the capability of the host to perform a hazard avoidance action on time to prevent the hazard from occurring. In (1), as a first approximation, it is assumed that $\{\mathcal{H}\}$ and $\{\mathcal{A}\}$ are independent events. However, it is clear that the more capable the host is of avoiding a hazard, the lower the latter's likelihood. Nevertheless, note that even when $\mathrm{P}\{\mathcal{A}\} = 1$, $\mathrm{P}\{\mathcal{H}\} > 0$ since the hazard likelihood does not depend solely on the hosts actions. ⧫

Finally, if the host faces more than one hazard simultaneously (see Figure 2), (1) can be extended as follows

$$S(T) = 1 - R(T) \triangleq \sum_i \mathrm{P}\{\mathcal{H}_i\}(1 - \mathrm{P}\{\mathcal{A}_i\})\mathrm{P}\{\mathcal{I}_i|\mathcal{H}_i\}, \tag{2}$$

where each $\mathcal{H}_\rangle$, $i = 1, 2, \cdots$, denotes a separate independent hazard (under the assumption that hazards can be treated independently).

The rest of the document will focus only on collision hazards and will present a method to estimate $P\{\mathcal{H}\}$. Details on how to estimate the probability of injury given specific collision conditions can be found in [22]. Methods to estimate collision avoidance capabilities are currently under investigation and will be presented elsewhere.

ON PROBABILITY OF COLLISION

As mentioned in the previous section, $\mathrm{P}\{\mathcal{H}\}$ represents the host's uncertainty in determining whether a collision will occur in a give timeframe. It arises due to: 1) imprecisions in the host's sensor measurements and 2) the uncertainty associated with predicting the *future* behavior of other traffic participants (called *targets*) relative to the host.

The general approach used to estimate $\mathrm{P}\{\mathcal{H}\}$ is as follows:

- The host's perception system measure or derives kinematic quantities like host/target positions, headings, lengths and widths, etc.
- These quantities, together with behavioral assumptions on both the host and target, are used to infer the relative positions of the host and target in the future T seconds[5].
- Determine if the target and host overlap.

Typical behavioral assumptions used to estimate future host/target behavior are that they either move with constant speed or with constant acceleration (see [9]). This allows one estimate both their future relative positions and their associated probability density functions. From this information one can infer the probability density function of the host/target overlap. Determining whether two vehicles overlap is akin to determining whether two convex polygons intersect. This is discussed next.

On Intersections of Convex Polygons

The main tool used to analyze whether two convex sets intersect is called the Separating Hyperplane Theorem (SHT, see [23]).

Theorem 1 (SHT). *Suppose C and D are nonempty disjoint convex sets, i.e., $C \cap D = \phi$. Then, there exists $a \neq 0$ and b such that $a^T x \leq b$ for all $x \in C$ and $a^T x \geq b$ for all $x \in D$.*

The proof of this theorem is constructive (see [23, p. 46]) and can be used to extend the theorem in several ways by adding additional conditions to the sets C and D as shown next (see [24, 25]):

Lemma 2. *Suppose $C, D \in \mathbb{R}^n$ are nonempty, closed, convex sets, at least one of which is bounded, and are such that $C \cap D = \phi$. Then, there exists $a \neq 0$ and b such that $a^T x < b$ for all $x \in C$ and $a^T x > b$ for all $x \in D$.*

The converse of these theorems seems to be true for finite dimensional spaces (like $\mathbb{R}^n$), though no formal proof has been found. In the finite dimensional case, using the additional concept of "separating axis" (i.e., a line perpendicular to a separating hyperplane) the following corollary of the Separating Hyperplane Theorem can be stated:

Lemma 3 (Separating Axis Theorem (SAT)). *Let $C, D \in \mathbb{R}^n$ be nonempty, closed, convex sets. If there exists a line L for which the projections of C and D, respectively $P_L(C)$ and $P_L(D)$, onto it do not intersect, then the $C \cap D = \phi$.*

SAT is stated without proof by most authors (although a proof is reportedly available in [26]). This corollary does not show how to find L so one presumably would have to identify it by inspection or by trial and error. Fortunately, in the case of convex polygons, the search space for L can be narrowed significantly. To do this, let L be defined as follows:

$$L \triangleq \{x \in \mathbb{R}^2 | x = a + t\hat{v}, \quad t \in (-\infty, \infty)\},$$

[5] More precisely, one should estimate the positions of the host and the target at time $\min\{TTC, T\}$, where TTC denotes the time to collision [15]

where a is a point in $\mathbb{R}^2$ and $\hat{v}$ is a unitary vector in the desired direction of L. Further, let the operator P_L be defined as follows:

$$P_L : \mathbb{R}^2 \to \mathbb{R}^2$$
$$x \mapsto a + \langle x - a, \hat{v} \rangle \hat{v},$$

where $\langle .,. \rangle$ denotes the standard inner product. $P_L(x)$ returns the location of the orthogonal projection of x on L. This concept can be extended to a set $C \subset \mathbb{R}^2$, with a slight abuse of notation, as follows:

$$P_L(C) \triangleq \{y \in R^2 | y = P_L(x), x \in C\}$$

The next result then follows (see [27, sec. 7.7.2]).

Corollary 4 (SAT for Convex Polygons)**.** *Let $C, D \in \mathbb{R}^n$ be $n-$ and $m-$sided convex polygons, respectively, and let S be a set of lines, each normal to a different edge of C and D. If there exist $L \in S$ such that $P_L(C) \cap P_L(D) = \phi$ then $C \cap D = \phi$.*

Note that S is not unique, since the translation of a separating axis is also a separating axis. Hence, it is sufficient for S to contains lines that cross the origin (i.e., for which $a = 0$). Also note that $P_L(C)$ and $P_L(D)$ are, by construction, line segments.

Detection of Vehicle Collision

To apply the results of the previous subsection to determining whether two vehicle overlap (i.e., have collided), consider the setup in Figure 3, which shows a host and a target. All coordinates in this figure are measured with respect to an arbitrary, fixed, ground coordinate system $\{G\}$. The figure's nomenclature is given in Table 1.

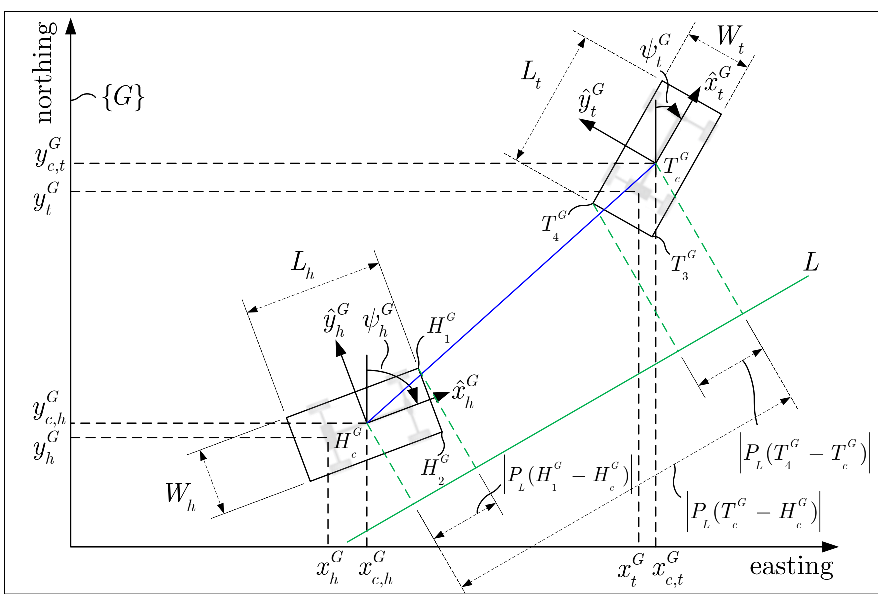

Figure 3: Coordinate framework for collision detection showing a host and a target vehicle.

To determine whether the host and target overlap, one can apply the SAT for convex polygons. Thus, assume that in Figure 3 the line L is a separating axis. Theorem 1 and Lemma 3 imply that

$$P_L(\text{Host}) \cap P_L(\text{Target}) = \phi \iff |P_L(T_c^G - H_c^G)| > 1/2|P_L(\text{Host})| + 1/2|P_L(\text{Target})|. \quad (3)$$

That is, the host and the target *do not collide* if the right hand side on the expression above holds[6]. The latter can be expanded as follows:

$$|P_L(T_c^G - H_c^G)| > \max\{|P_L(H_1^G - H_c^G)|, |P_L(H_2^G - H_c^G)|\} + \max\{|P_L(T_4^G - T_c^G)|, |P_L(T_3^G - T_c^G)|\}. \quad (4)$$

This inequality can be expressed in term of the variables shown in Figure 3 by noticing that

$$|P_L(H_1^G - H_c^G)| = |\langle H_1^G - H_c^G, \hat{v}\rangle\hat{v}| = |\langle L_h/2\hat{x}^H + W_h/2\hat{y}^H, \hat{v}\rangle|,$$

and that

$$\begin{aligned} |P_L(H_2^G - H_c^G)| &= |\langle L_h/2\hat{x}^H - W_h/2\hat{y}^H, \hat{v}\rangle|, \\ |P_L(T_4^G - T_c^G)| &= |\langle -L_t/2\hat{x}^T + W_t/2\hat{y}^T, \hat{v}\rangle|, \\ |P_L(T_3^G - T_c^G)| &= |\langle -L_t/2\hat{x}^T - W_t/2\hat{y}^T, \hat{v}\rangle|. \end{aligned}$$

Thus, condition (4) is equivalent to

$$\begin{aligned} |P_L(T_c^G - H_c^G)| > \max\{&|\langle L_h/2\hat{x}^H + W_h/2\hat{y}^H, \hat{v}\rangle|, |\langle L_h/2\hat{x}^H - W_h/2\hat{y}^H, \hat{v}\rangle|\} \\ &+ \max\{|\langle L_t/2\hat{x}^T + W_t/2\hat{y}^T, \hat{v}\rangle|, |\langle L_t/2\hat{x}^T - W_t/2\hat{y}^T, \hat{v}\rangle|\}. \quad (5) \end{aligned}$$

According to Corollary 4, it is sufficient to limit the search for a line L that would fulfill (5) to those parallel to the sides of the host and target vehicles. If no one if these lines satisfies (5), then the host and target vehicles overlap. This leads to the following result.

Corollary 5. *The host and target vehicles shown in Figure 3* do not *collide if and only if* any *the following four conditions holds:*

$$\begin{aligned} |\langle T_c^G - H_c^G, \hat{x}_h^G\rangle| &> L_h/2 + \max\{|\langle L_t/2\hat{x}_t^G + W_t/2\hat{y}_t^G, \hat{x}_h^G\rangle|, |\langle L_t/2\hat{x}_t^G - W_t/2\hat{y}_t^G, \hat{x}_h^G\rangle|\}, \\ |\langle T_c^G - H_c^G, \hat{y}_h^G\rangle| &> W_h/2 + \max\{|\langle L_t/2\hat{x}_t^G + W_t/2\hat{y}_t^G, \hat{y}_h^G\rangle|, |\langle L_t/2\hat{x}_t^G - W_t/2\hat{y}_t^G, \hat{y}_h^G\rangle|\}, \\ |\langle T_c^G - H_c^G, \hat{x}_t^G\rangle| &> L_t/2 + \max\{|\langle L_h/2\hat{x}_h^G + W_h/2\hat{y}_h^G, \hat{x}_t^G\rangle|, |\langle L_h/2\hat{x}_h^G - W_h/2\hat{y}_h^G, \hat{x}_t^G\rangle|\}, \\ |\langle T_c^G - H_c^G, \hat{y}_t^G\rangle| &> W_t/2 + \max\{|\langle L_h/2\hat{x}_h^G + W_h/2\hat{y}_h^G, \hat{y}_t^G\rangle|, |\langle L_h/2\hat{x}_h^G - W_h/2\hat{y}_h^G, \hat{y}_t^G\rangle|\}. \end{aligned}$$

Proof: This result follows directly from Theorem 1 and Corollary 4. ∎

The inequalities in Corollary 5 can be simplified by using a more conservative definition of "non-collision" conditions as follows.

Corollary 6. *The host and target vehicles shown in Figure 3* do not *collide if* any *the following four conditions holds:*

$$|\langle T_c^G - H_c^G, \hat{x}_h^G\rangle| > \left(L_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2, \quad (6)$$

$$|\langle T_c^G - H_c^G, \hat{y}_h^G\rangle| > \left(W_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2, \quad (7)$$

$$|\langle T_c^G - H_c^G, \hat{x}_t^G\rangle| > \left(L_t + \sqrt{(L_h)^2 + (W_h)^2}\right)/2, \quad (8)$$

$$|\langle T_c^G - H_c^G, \hat{y}_t^G\rangle| > \left(W_t + \sqrt{(L_h)^2 + (W_h)^2}\right)/2. \quad (9)$$

Although simpler, conditions (6)-(9) are more conservative. That is, a host and a target may not satisfy these condition and still not be in collision. As it will be seen next, these leads to an over estimation of the probability of collision.

[6]The inequality in (3) is often stated as a "greater or equal" inequality, to allow for the fact that the vehicles may share common edge (i.e., just touch). Here, a "more than" inequality is used to guarantee full separation between vehicles.

[1]The world currently outputs the position of the center of a vehicle's back axel (host or target). Here it is assumed that, in the future, the world model will also output the length, L, and width, W, every target vehicle.

Table 1: Figure 3 nomenclature.

	Signal	Explanation	Unit
Target	$T_c^G = (x_{c,t}^G, y_{c,t}^G)$	Target geometric center position w.r.t. $\{G\}$	m,m
	$x_{c,t}^G$	Target geometrical center[1] easting position	m
	$y_{c,t}^G$	Target geometrical center northing position	m
	x_t^G	Target rear axle center easting position	m
	y_t^G	Target rear axle center northing position	m
	ψ_t^G	Target rear axle heading (clockwise positive)	rad
	$\hat{x}_t^G$	Unitary vector parallel to the Target's heading in $\{G\}$ coordinates	
	$\hat{y}_t^G$	Unitary vector perpendicular to the Target's heading in $\{G\}$ coordinates	
	L_t	Target vehicle's length	m
	W_t	Target vehicle's width	m
	T_3^G (T_4^G)	Target vehicle's back right (left) corner position w.r.t. $\{G\}$	m,m
Host	$H_c^G = (x_{c,h}^G, y_{c,h}^G)$	Host geometric center position w.r.t. $\{G\}$	m,m
	$x_{c,h}^G$	Host geometrical center[1] easting position	m
	$y_{c,h}^G$	Host geometrical center northing position	m
	x_h^G	Host rear axle center easting position	m
	y_h^G	Host rear axle center northing position	m
	ψ_h^G	Host rear axle heading (clockwise positive)	rad
	$\hat{x}_h^G$	Unitary vector parallel to the Host's heading in $\{G\}$ coordinates	
	$\hat{y}_h^G$	Unitary vector perpendicular to the Host's heading in $\{G\}$ coordinates	
	L_h	Host vehicle's length	m
	W_h	Host vehicle's width	m
	H_1^G (H_2^G)	Host vehicle's front right (left) corner position w.r.t. $\{G\}$	m,m
Projections	L	Separating axis candidate	
	$\|P_L(T_c^G - H_c^G)\|$	Projection magnitude of vector $T_c^G - H_c^G$ over L	m
	$\|P_L(H_1^G - H_c^G)\|$	Projection magnitude of vector $H_1^G - H_c^G$ over L	m
	$\|P_L(T_4^G - T_c^G)\|$	Projection magnitude of vector $T_4^G - T_c^G$ over L	m

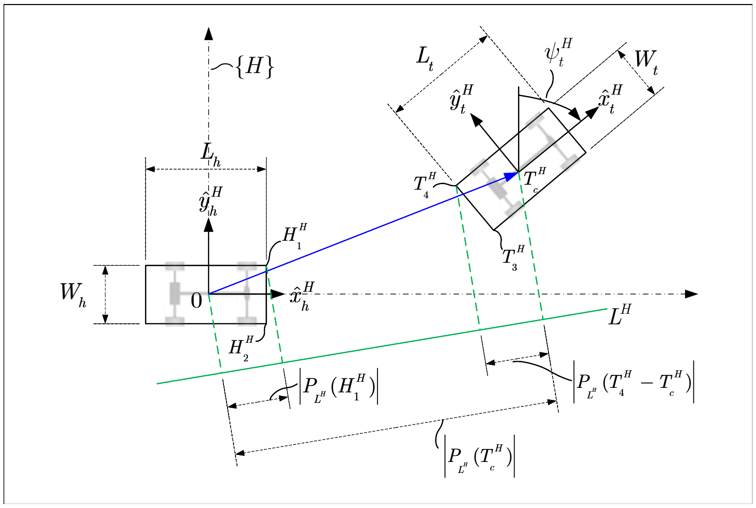

Figure 4: Host coordinate framework for collision detection showing a host and a target vehicle. The variables are defined as in Table 1, replacing the superscript ^{G} with ^{H}.

Estimation of Probability of Collision

The estimation of probability of collision is performed by the host vehicle based on measurements provided by its perception system. These measurements include the target position w.r.t. the host, T_c^H, and the target's heading w.r.t., ψ_t^H, and assume the frame of reference shown in Figure 4 (a rotated version of Figure 3). It follows from this figure that:

$$H_c^H = 0, \quad \hat{x}_h^H = (1,0), \quad \hat{y}_h^H = (0,1), \quad \hat{x}_t^H = (\sin(\phi_t^H), \cos(\phi_t^H)), \quad \hat{y}_t^H = (-\cos(\phi_t^H), \sin(\phi_t^H)).$$

As mentioned before, the uncertainty associated with the host vehicle sensor measurements and the predictions of future host/target behavior is what makes checking (6)-(9) non-deterministic. The uncertain sensor measurements can be treated as random variables with associated Probability Density Functions (PDFs). These variables will be denoted in the sequel in boldface fonts. The primary sensor measures, upon which any other quantities are derived, are listed next.

Assumption 1. *The following (primary) quantities are assumed to be independent random variables defined over the probability space* $(\Omega, \mathscr{F}, \mathrm{P})$. *They are shown with their associated PDFs.*

$$\boldsymbol{T}_c^H = (\boldsymbol{x}_{c,t}^H, \boldsymbol{y}_{c,t}^H) \sim f_{T_c} = f_{x_{c,t}} f_{y_{c,t}}, \quad \text{where} \quad \boldsymbol{x}_{c,t}^H \sim f_{x_{c,t}} \quad \text{and} \quad \boldsymbol{y}_{c,t}^H \sim f_{y_{c,t}}$$
$$\boldsymbol{\psi}_t^H \sim f_{\psi_t}, \quad \boldsymbol{L}_t \sim f_{L_t}, \quad \boldsymbol{W}_t \sim f_{W_t}.$$

Since current automated vehicle not in general have the ability of directly estimating W_t or L_t from sensor measurements, the following assumption will be accepted as true in the sequel.

Assumption 2. *The target's size is communicated via vehicle-to-vehicle communication to the host.*

These assumptions and conditions (6)-(9) can be used to derive an over-estimate of the probability of collision as follows: Let $C_1, C_2, C_3, C_4 \subset \Omega$ be the following events

$$C_1 \triangleq \{\omega \in \Omega \mid |\boldsymbol{x}_{c,t}^H| > \left(L_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2\},$$
$$C_2 \triangleq \{\omega \in \Omega \mid |\boldsymbol{y}_{c,t}^H| > \left(W_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2\},$$
$$C_3 \triangleq \{\omega \in \Omega \mid |\boldsymbol{x}_{c,t}^H \sin(\boldsymbol{\psi}_t^h) + \boldsymbol{y}_{c,t}^H \cos(\boldsymbol{\psi}_t^h)| > \left(L_t + \sqrt{(L_h)^2 + (W_h)^2}\right)/2\},$$
$$C_4 \triangleq \{\omega \in \Omega \mid |\boldsymbol{x}_{c,t}^H \cos(\boldsymbol{\psi}_t^h) - \boldsymbol{y}_{c,t}^H \sin(\boldsymbol{\psi}_t^h)| > \left(W_t + \sqrt{(L_h)^2 + (W_h)^2}\right)/2\}.$$

Further, let $A \subset \Omega$ be the event "host and target do not collide" defined according to Corollary 6. That is, $A \triangleq \left\{\omega \in \Omega \mid \omega \in \bigcup_{i=1}^{4} C_i\right\}$. It follows from this definition and from De Morgan's laws that $\bar{A} \triangleq \Omega - A$, the "host and target collide" event, is given by:$\bar{A} \triangleq \left\{\omega \in \Omega | \omega \in \bigcap_{i=1}^{4} \bar{C}_i\right\}$, where $\bar{C}_i = \Omega - C_i$, $i = 1, \cdots, 4$. This lead to the following result

Theorem 7. *Consider the host and target vehicle in Figure 4. Under Assumptions 1 and 2, the probability of collision between the host and target,* $\mathrm{P}\{\mathcal{H}\}$ *can be* overestimated *as follows:*

$$\mathrm{P}\{\mathcal{H}\} = \mathrm{P}\{\text{“Host-Target Collide”}\} \leq \mathrm{P}\{\omega \in \Omega \mid \omega \in \bar{A}\} = \mathrm{P}\{(\boldsymbol{x}_{c,t}^H, \boldsymbol{y}_{c,t}^H, \boldsymbol{\psi}_t^H) \in R_1 \cap R_2(\boldsymbol{\psi}_t^H) \times [0, 2\pi)\},$$

where $R_1, R_2(\boldsymbol{\psi}_t^H) \subset \mathbb{R}^2$ *are rectangular regions in* $\mathbb{R}^2$ *given, respectively, by:*

$$R_1 \triangleq \{(x, y) \in \mathbb{R}^2 \mid |x| \leq 0.5(L_h + \sqrt{(L_t)^2 + (W_t)^2}), |y| \leq 0.5(W_h + \sqrt{(L_t)^2 + (W_t)^2})\},$$

and

$$R_2(\boldsymbol{\psi}_t^H) \triangleq \left\{(x, y) \in \mathbb{R}^2 \mid (x, y) = r \begin{bmatrix} \sin(\boldsymbol{\psi}_t^H) \\ \cos(\boldsymbol{\psi}_t^H) \end{bmatrix} + s \begin{bmatrix} \cos(\boldsymbol{\psi}_t^H) \\ -\sin(\boldsymbol{\psi}_t^H) \end{bmatrix}; \right. \\ \left. |r| \leq 0.5(L_t + \sqrt{(L_h)^2 + (W_h)^2}), |s| \leq 0.5(W_t + \sqrt{(L_h)^2 + (W_h)^2}) \right\}.$$

Proof: Recall that A is defined based on conditions (6)-(9). Since these are conservative, it follows that A is a subset of the event "Host and Target do not Collide". This in turn implies that $\mathrm{P}\{\text{“Host-Target Collide”}\} \leq \mathrm{P}\{\omega \in \Omega \mid \omega \in \bar{A}\}$. Next, observe from the definition of A that

$$\bar{A} = \left\{\omega \in \Omega | \omega \in (\bar{C}_1 \cap \bar{C}_2) \cap (\bar{C}_3 \cap \bar{C}_4) \cap \Omega\right\}. \tag{10}$$

The three terms in the RHS of the expression above can be further developed.

$$\begin{aligned} \bar{C}_1 \cap \bar{C}_2 &= \left\{\omega \in \Omega \mid |\boldsymbol{x}_{c,t}^H| \leq \left(L_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2\right\} \\ &\qquad \bigcap \left\{\omega \in \Omega \mid |\boldsymbol{y}_{c,t}^H| \leq \left(W_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2\right\} \\ &= \left\{\omega \in \Omega \mid |\boldsymbol{x}_{c,t}^H| \leq \left(L_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2, |\boldsymbol{y}_{c,t}^H| \leq \left(W_h + \sqrt{(L_t)^2 + (W_t)^2}\right)/2\right\} \\ &= \left\{\omega \in \Omega \mid (\boldsymbol{x}_{c,t}^H, \boldsymbol{y}_{c,t}^H) \in R_1\right\}. \end{aligned} \tag{11}$$

Similarly:

$$(\bar{C}_3 \cap \bar{C}_4) \cap \Omega = (\bar{C}_3 \cap \bar{C}_4) \cap \{\omega \in \Omega \mid \boldsymbol{\psi}_t^H \in [0, 2\pi)\}$$

and

$$(\bar{C}_3 \cap \bar{C}_4) = \{\omega \in \Omega \mid |\boldsymbol{x}_{c,t}^H \sin(\boldsymbol{\psi}_t^h) + \boldsymbol{y}_{c,t}^H \cos(\boldsymbol{\psi}_t^h)| \leq \left(L_t + \sqrt{(L_h)^2 + (W_h)^2}\right)/2, \\ |\boldsymbol{x}_{c,t}^H \cos(\boldsymbol{\psi}_t^h) - \boldsymbol{y}_{c,t}^H \sin(\boldsymbol{\psi}_t^h)| \leq \left(W_t + \sqrt{(L_h)^2 + (W_h)^2}\right)/2\}.$$

The above expression can be further developed by letting $\boldsymbol{r} = \boldsymbol{x}_{c,t}^H \sin(\boldsymbol{\psi}_t^h) + \boldsymbol{y}_{c,t}^H \cos(\boldsymbol{\psi}_t^h)$ and $\boldsymbol{s} = \boldsymbol{x}_{c,t}^H \cos(\boldsymbol{\psi}_t^h) - \boldsymbol{y}_{c,t}^H \sin(\boldsymbol{\psi}_t^h)$, and observing that

$$\begin{bmatrix} \boldsymbol{r} \\ \boldsymbol{s} \end{bmatrix} = \begin{bmatrix} \sin(\boldsymbol{\psi}_t^h) & \cos(\boldsymbol{\psi}_t^h) \\ \cos(\boldsymbol{\psi}_t^h) & -\sin(\boldsymbol{\psi}_t^h) \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_{c,t}^H \\ \boldsymbol{y}_{c,t}^H \end{bmatrix},$$

so

$$\begin{bmatrix} \boldsymbol{x}_{c,t}^H \\ \boldsymbol{y}_{c,t}^H \end{bmatrix} = \begin{bmatrix} \sin(\boldsymbol{\psi}_t^h) & \cos(\boldsymbol{\psi}_t^h) \\ \cos(\boldsymbol{\psi}_t^h) & -\sin(\boldsymbol{\psi}_t^h) \end{bmatrix} \begin{bmatrix} \boldsymbol{r} \\ \boldsymbol{s} \end{bmatrix} = \boldsymbol{r} \begin{bmatrix} \sin(\boldsymbol{\psi}_t^h) \\ \cos(\boldsymbol{\psi}_t^h) \end{bmatrix} + \boldsymbol{s} \begin{bmatrix} \cos(\boldsymbol{\psi}_t^h) \\ -\sin(\boldsymbol{\psi}_t^h) \end{bmatrix}.$$

This implies that

$$(\bar{C}_3 \cap \bar{C}_4) \cap \Omega = \Big\{ \omega \in \Omega \mid \begin{bmatrix} \boldsymbol{x}^H_{c,t} \\ \boldsymbol{y}^H_{c,t} \end{bmatrix} = \boldsymbol{r} \begin{bmatrix} \sin(\boldsymbol{\psi}^h_t) \\ \cos(\boldsymbol{\psi}^h_t) \end{bmatrix} + \boldsymbol{s} \begin{bmatrix} \cos(\boldsymbol{\psi}^h_t) \\ -\sin(\boldsymbol{\psi}^h_t) \end{bmatrix}, \\ |\boldsymbol{r}| \leq 0.5(L_t + \sqrt{(L_h)^2 + (W_h)^2}), |\boldsymbol{s}| \leq 0.5(W_t + \sqrt{(L_h)^2 + (W_h)^2}); \boldsymbol{\psi}^H_t \in [0, 2\pi) \Big\}$$

or, equivalently, that

$$(\bar{C}_3 \cap \bar{C}_4) \cap \Omega = \Big\{ \omega \in \Omega \mid (\boldsymbol{x}^H_{c,t}, \boldsymbol{y}^H_{c,t}) \in R_2(\boldsymbol{\psi}^H_t); \psi^H_t \in [0, 2\pi) \Big\}. \tag{12}$$

Replacing (11)-(12) into (10) yields

$$\begin{aligned} A &= \Big\{ \omega \in \Omega \mid (\boldsymbol{x}^H_{c,t}, \boldsymbol{y}^H_{c,t}) \in R_1 \cap R_2(\boldsymbol{\psi}^H_t); \psi^H_t \in [0, 2\pi) \Big\} \\ &= \Big\{ \omega \in \Omega \mid (\boldsymbol{x}^H_{c,t}, \boldsymbol{y}^H_{c,t}, \boldsymbol{\psi}^H_t) \in R_1 \cap R_2(\boldsymbol{\psi}^H_t) \times [0, 2\pi) \Big\}, \end{aligned}$$

which proves the Theorem. ∎

To end this section, we provide a numerical implementation of the results in Theorem 7.

A Numerical Implementation

The goal here is to compute $\mathrm{P}\{(\boldsymbol{x}^H_{c,t}, \boldsymbol{y}^H_{c,t}) \in R_1 \cap R_2(\boldsymbol{\psi}^H_t); \boldsymbol{\psi}^H_t \in [0, 2\pi)\}$. Formally,

$$\mathrm{P}\{(\boldsymbol{x}^H_{c,t}, \boldsymbol{y}^H_{c,t}) \in R_1 \cap R_2(\boldsymbol{\psi}^H_t); \boldsymbol{\psi}^H_t \in [0, 2\pi)\} \\ = \iiint 1_{\{(x,y,\psi) \in R_1 \cap R_2(\boldsymbol{\psi}^H_t) \times \in [0,2\pi)\}} f_{x_{c,t}, y_{c,t}, \psi_t} \mathrm{d}x\mathrm{d}y\mathrm{d}\psi.$$

Under Assumption 1, the above expression can be further simplified as follows:

$$\mathrm{P}\{(\boldsymbol{x}^H_{c,t}, \boldsymbol{y}^H_{c,t}) \in R_1 \cap R_2(\boldsymbol{\psi}^H_t); \boldsymbol{\psi}^H_t \in [0, 2\pi)\} \\ = \int 1_{\{\psi \in [0,2\pi)\}} \left(\iint 1_{\{(x,y,\psi) \in R_1 \cap R_2(\boldsymbol{\psi}^H_t)\}} f_{x_{c,t}, y_{c,t}} \mathrm{d}x\mathrm{d}y \right) f_{\psi_t} \mathrm{d}\psi. \tag{13}$$

To further simplify the expression above, knowledge of the specific type of distributions for each random variable would be needed. In the absence of emperical information, the following assumption will be made:

Assumption 3. $\boldsymbol{x}^H_{c,t}$, $\boldsymbol{y}^H_{c,t}$, *and* $\boldsymbol{\psi}^H_t$ *are uniformly distributed random variables.*

Since the world model provides estimates of the mean, μ, and variance, σ^2, for each measured variable, the probability density functions associated with $\boldsymbol{x}^H_{c,t}$, $\boldsymbol{y}^H_{c,t}$, and $\boldsymbol{\psi}^H_t \boldsymbol{x}^H_{c,t}$, $\boldsymbol{y}^H_{c,t}$, and $\boldsymbol{\psi}^H_t$ are given by:

$$\begin{aligned} f_{x_{c,t}} &= \frac{1}{\sqrt{12}\sigma_{x^H_{c,t}}} 1_{\{x \in [\mu_{x^H_{c,t}} - \sqrt{3}\sigma_{x^H_{c,t}}, \mu_{x^H_{c,t}} + \sqrt{3}\sigma_{x^H_{c,t}}]\}}, \\ f_{y_{c,t}} &= \frac{1}{\sqrt{12}\sigma_{y^H_{c,t}}} 1_{\{y \in [\mu_{y^H_{c,t}} - \sqrt{3}\sigma_{y^H_{c,t}}, \mu_{y^H_{c,t}} + \sqrt{3}\sigma_{y^H_{c,t}}]\}}, \end{aligned}$$

and

$$f_{\psi_t} = \frac{1}{\sqrt{12}\sigma_{\psi^H_t}} 1_{\{\psi \in [\mu_{\psi^H_t} - \sqrt{3}\sigma_{\psi^H_t}, \mu_{\psi^H_t} + \sqrt{3}\sigma_{\psi^H_t}]\}}.$$

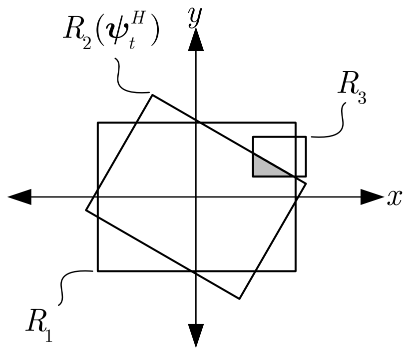

Figure 5: The gray area shows the region of integration associated with (14).

Replacing the above functions in (13) yields, after a few manipulations, the following:

$$\mathrm{P}\{(\boldsymbol{x}_{c,t}^H, \boldsymbol{y}_{c,t}^H) \in R_1 \cap R_2(\boldsymbol{\psi}_t^H)\boldsymbol{\psi}_t^H \in [0, 2\pi)\}$$
$$= \frac{1}{12\sqrt{12}\sigma_{x_{c,t}^H}\sigma_{y_{c,t}^H}\sigma_{\psi_t^H}} \int_{\mu_{\psi_t^H}-\sqrt{3}\sigma_{\psi_t^H}}^{\mu_{\psi_t^H}+\sqrt{3}\sigma_{\psi_t^H}} \left(\iint 1_{\{(x,y,\psi)\in R_1\cap R_2(\psi)\cap R_3\}} \mathrm{d}x\mathrm{d}y\right) \mathrm{d}\psi, \quad (14)$$

where $R_3 \subset \mathbb{R}^2$ is the rectangular subset of $\mathbb{R}^2$ given by:

$$R_3 \triangleq \{(x, y) \in \mathbb{R}^2 \mid x \in [\mu_{x_{c,t}^H} - \sqrt{3}\sigma_{x_{c,t}^H}, \mu_{x_{c,t}^H} + \sqrt{3}\sigma_{x_{c,t}^H}], y \in [\mu_{y_{c,t}^H} - \sqrt{3}\sigma_{y_{c,t}^H}, \mu_{y_{c,t}^H} + \sqrt{3}\sigma_{y_{c,t}^H}]\}.$$

Note that the expression between parenthesis in (14) is the area of the polygon created by intersecting R_1, $R_2(\psi)$, and R_3 (the intesection could also be empty). An example of this intersection is shown in Figure 5. Let $m(R_1 \cap R_2(\psi) \cap R_3)$ denote this area and observe that it is a function of the angle ψ. Although a formula could be derived to compute this area as a function of ψ, such an expression would not provide more insights or lead to simplifications. Hence, a numerical approach is better suited to compute (14).

To this end, let $1 \leq n \in \mathbb{Z}^+$ and set $\psi_i = \mu_{\psi_t^H} + \sqrt{3}\sigma_{\psi_t^H}\left(\frac{2i}{n} - 1\right)$, $i = 0, \ldots, n-1$. The right hand side of (14) can now be approximated as follows:

$$\mathrm{P}\{(\boldsymbol{x}_{c,t}^H, \boldsymbol{y}_{c,t}^H) \in R_1 \cap R_2(\boldsymbol{\psi}_t^H)\boldsymbol{\psi}_t^H \in [0, 2\pi)\} \approx \frac{1}{12n\sigma_{x_{c,t}^H}\sigma_{y_{c,t}^H}} \sum_{i=0}^{n-1} m(R_1 \cap R_2(\psi_i) \cap R_3) \quad (15)$$

where, for every ψ_i, $m(R_1 \cap R_2(\psi_i) \cap R_3)$ can be computed using standard functions for polygon intersection (see, e.g., Sutherland-Hodgman Polynomial Clipping Algorithm in [28]) and polygon area [29]. The calculation of (15) can be performed numerically by implementing Algorithm 1.

CONCLUSIONS

This article proposed a methodology to compute the "safety" of a vehicle quantitatively, so it can be used by automated vehicle for decision making and control. The methodology treats each interaction a vehicle has with other road user and road interactions as potential hazards and assigns each value of risk. The risk a hazard imposes on the vehicle in derived from the hazard's likelihood, hazardousness, and from the capability of the vehicle to avoid it. The article also offered a theoretical method to estimate the likelihood of two-dimensional collision hazards (an extension of the work in [9]) and recommendations on how to estimate hazard hazardousness.

Algorithm 1 InSTProbColEstimator: Instantaneous, Single Target, Host-Target Probability of Collision Estimator

Require: $W_h > 0, L_h > 0, W_t > 0, L_t > 0$ {host & target dimensions}
Require: $x^H_{c,t}, y^H_{c,t}, \sigma_{x^H_{c,t}} \geq 0, \sigma_{y^H_{c,t}} \geq 0$ {mean and variance of the target position w.r.t. the host}
Require: $\psi^H_t, \sigma_{\psi^H_t} \geq 0$ {mean and variance of the target's heading w.r.t. the host's vertical axis}
Require: $n \geq 1$ {number of discretization points for the range of $\boldsymbol{\psi}^H_t$ }
Ensure: $PCol$ = Probability of Collision

$PCol \leftarrow 0$ {$PCol$ is zero by default}

$R_1 \leftarrow \begin{bmatrix} -0.5(L_h+\sqrt{(L_t)^2+(W_t)^2}) & -0.5(W_h+\sqrt{(L_t)^2+(W_t)^2}) \\ 0.5(L_h+\sqrt{(L_t)^2+(W_t)^2}) & -0.5(W_h+\sqrt{(L_t)^2+(W_t)^2}) \\ 0.5(L_h+\sqrt{(L_t)^2+(W_t)^2}) & 0.5(W_h+\sqrt{(L_t)^2+(W_t)^2}) \\ -0.5(L_h+\sqrt{(L_t)^2+(W_t)^2}) & 0.5(W_h+\sqrt{(L_t)^2+(W_t)^2}) \end{bmatrix}$ {R_1 vertices, counterclockwise (CCW)}

$R_3 \leftarrow \begin{bmatrix} x^H_{c,t}-\sqrt{3}\sigma_{x^H_{c,t}} & y^H_{c,t}-\sqrt{3}\sigma_{y^H_{c,t}} \\ x^H_{c,t}+\sqrt{3}\sigma_{x^H_{c,t}} & y^H_{c,t}-\sqrt{3}\sigma_{y^H_{c,t}} \\ x^H_{c,t}+\sqrt{3}\sigma_{x^H_{c,t}} & y^H_{c,t}+\sqrt{3}\sigma_{y^H_{c,t}} \\ x^H_{c,t}-\sqrt{3}\sigma_{x^H_{c,t}} & y^H_{c,t}+\sqrt{3}\sigma_{y^H_{c,t}} \end{bmatrix}$ {R_3 vertices, CCW}

$[RisEmpty, R] \leftarrow PolyIntersect(R_1, R_3)$ {R: $R_1 \cap R_3$ CCW vertices. If empty, $RisEmpty = 1$}
if $\neg RisEmpty$ **then**
  for $i = 0$ to $n-1$ **do**
    $\psi \leftarrow \psi^H_t + \sqrt{3}\sigma_{\psi^H_t}\left(\frac{2i}{n} - 1\right)$

$R_2 \leftarrow \begin{bmatrix} -0.5(L_t+\sqrt{(L_h)^2+(W_h)^2}) & 0.5(W_t+\sqrt{(L_h)^2+(W_h)^2}) \\ -0.5(L_t+\sqrt{(L_h)^2+(W_h)^2}) & -0.5(W_t+\sqrt{(L_h)^2+(W_h)^2}) \\ 0.5(L_t+\sqrt{(L_h)^2+(W_h)^2}) & -0.5(W_t+\sqrt{(L_h)^2+(W_h)^2}) \\ 0.5(L_t+\sqrt{(L_h)^2+(W_h)^2}) & 0.5(W_t+\sqrt{(L_h)^2+(W_h)^2}) \end{bmatrix} \begin{bmatrix} \sin(\psi) & \cos(\psi) \\ -\cos(\psi) & \sin(\psi) \end{bmatrix}$ {$R_2(\psi_i)$ CCW vertices}

    $[R_aEmpty, R_a] \leftarrow PolyIntersect(R, R_2)$ {R_a:$R_1 \cap R_3 \cap R_2(\psi)$ CCW vertices. If empty, $R_aEmpty = 1$}

    if $\neg R_aEmpty$ **then**
      $PCol \leftarrow PCol + PolyArea(R_a)$
    end if
  end for
  $PCol \leftarrow PCol/(12n\sigma_{x^H_{c,t}}\sigma_{y^H_{c,t}})$
end if

Further work is required to link the likelihood estimator with motion predictor models, and to validated the complete methodology first by detailed simulations and they by experimentation.

Acknowledgements

The authors would like to thank Stefanie Hair-Buijssen (TNO), Richard van der Horst, Aliaksei Laureshyn (Lund University), Erwin de Gelder (TNO), Jan-Pieter Paardekooper (TNO), Ron Snijders (TNO), and Jeroen Manders (TNO) for important information and discussions that sharpened the ideas in this article.

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