Validation Methodology to Establish Safe Autonomous Driving Algorithms with a High Driver Acceptance Using a Virtual Environment

Hideo Inoue, Mohanad El-Haji, Thomas Freudenmann, Haipeng Zhang, Pongsathorn Raksincharoensak, Yuichi Saito

Kanagawa Institute of Technology (KAIT),
EDI GmbH – Engineering Data Intelligence,
Tokyo University of Agriculture and Technology (TUAT)

10-30 Shimoogino Atsugi, Kanagawa Prefecture, 243-0292, Japan
Phone: (+81) 70-2222-0633
E-mail: inoue@eng.kanagawa-it.ac.jp
1. Co-author's E-mail: el-haji@edi.gmbh
2. Co-author's E-mail: freudenmann@edi.gmbh
3. Co-author's E-mail: s1884006@cce.kanagawa-it.jp
4. Co-author's E-mail: pong@cc.tuat.ac.jp
5. Co-author's E-mail: y-saito@cc.tuat.ac.jp

Keyword(s): Driver behavior modeling, realistic traffic flow simulation, active safety systems, autonomous driving and ADAS algorithms, Dynamic Risk Management, Safety Cushion

Abstract

This paper introduces a validation methodology and a corresponding virtual environment for autonomous driving algorithms. The proposed method particularly differs from the state of the art since it is based on a deep analysis of real incident data recorded in Japan since 2004. This data is stored in the so called *Near-Miss Incident Data Base*. The analysis of more than 100.000 incidents specifically focused on the divers' decision-making process in critical traffic situations. In this context, the human anticipation of hazards plays an essential role to avoid accidents as well as uncomfortable situations. In doing so, human drivers mentally perform *Dynamic Risk Management* which depends on numerous driving context parameters. The relevant context parameters registered in the Near-Miss Incident Data Base were identified and quantified regarding their contribution to the criticality of a specific traffic situation. On this basis, a purposeful validation environment using the powerful traffic flow simulation software PTV Vissim has been built up. This allows the evaluation of new autonomous driving algorithms in virtual traffic scenarios with realistic distribution of critical situations. This validation environment can be used to identify new potentially dangerous situations in traffic as well as to calibrate the behavior of autonomous vehicles with respect to these scenarios, taking in account different customer preferences in driving behavior (defensive vs. sportive driving). The benefit of the proposed validation methodology and tools will be demonstrated by comparing the standard driver model of PTV Vissim with a novel concept of an autonomous driving algorithm that was developed based on the objectification of driver behavior of Japanese taxi drivers recorded in the Near-Miss Incident Data Base.

I. Challenges in the Development of Autonomous Driving Systems

Despite ongoing remarkable development efforts of OEMs and suppliers in the past years, intelligent active safety systems remain afflicted with uncertainties. With today's powerful sensor technology and sufficiently high computation power, these uncertainties relate less to data capture and processing but rather to the meaningful aggregation and combination of data from different sources in order to take effective – safe, acceptable and understandable – actions in traffic. This especially accounts for autonomous vehicles of high levels of automation (level 4 and level 5) that are required to interact with different types of not automated road users (bicycles, pedestrians, conventional vehicles, scooters etc.). Human factors have manifold influences on what is generally considered an *effective action* that leads to a safe and acceptable behavior of the autonomous vehicle depending on the context of the situation in traffic. Therefore, human behaviors and expectations towards other road users must be analyzed and understood for designing corresponding autonomous driving algorithms. This is especially challenging when considering children or elderly road users who often feature a behavior that is hard to predict, leading to situations in traffic in which serious injuries are frequent. [1] [2] [3]

Developing autonomous driving systems that can intelligently avoid potentially dangerous situations in traffic or – in case such a situation is inevitable – reliably detect the level of danger and perform suitable evasive actions that minimize the risk of injury for the driver as well as other road users requires extensive validation and testing efforts. Currently, developers of autonomous driving systems carry out field experiments to ensure the reliability and stability of their algorithms. Those field experiments are not only very time consuming and expensive; it is also nearly impossible to validate new algorithms in all possible traffic situations due to the uncountable combination possibilities of traffic context parameters (road type, area type, traffic opponent types etc.). Moreover, developers are required to evaluate different concepts of algorithms in early stages. Therefore, they need to conduct reproducible tests with controllable parameters in order to objectively judge the performance of their development efforts and – if necessary – search for alternative solutions. Both substantial aspects, reproducibility and controllability, are very hard to accomplish when conducting field experiments that require the interaction of multiple road users in different traffic situations. [4] [5]

For these reasons, the use of simulation tools for the development and validation of autonomous driving systems has been increasing significantly in the previous years. However, current approaches usually lack a sophisticated and realistic simulation of one of the most decisive validation criteria for new autonomous driving algorithms: the interaction of the system under development, e.g. a new autonomous driving algorithm, with conventional vehicles in a realistic traffic and infrastructure context. In this context, the trade-off between safety and driver acceptance is a decisive aspect that affects the algorithm quality. However, this trade-off decision is currently not sufficiently considered by today's validation methods and tools. Another aspect that needs more consideration regarding a holistic evaluation of new autonomous driving systems is the impact of their behavior on the traffic flow: It must be ensured that the actions of vehicles that feature a high level of automation do not lead more congestion and interact with other vehicles smoothly. [6]

In order to overcome these shortcomings, we propose a validation methodology and corresponding simulation environment for the development of autonomous driving systems that:

1. provides an efficient toolbox to model different combinations of traffic infrastructure properties and traffic opponent behaviors that have been identified as risky based on of the analysis of critical situations in real traffic.
2. allows the efficient and realistic modeling of driver behavior as well as traffic opponent behavior (pedestrian, bicycle etc.) in different traffic scenarios and reliably detects critical situations.
3. allows the statistical evaluation of the interaction of new algorithms in critical scenarios with realistic traffic according to various criteria (overall safety, driver acceptance, influence on traffic flow, etc.).

II. Foundation of the Proposed Methodology

A. Near-Miss Incident Data Base

The Near-Miss Incident Data Base has been constructed and managed by TUAT since 2004. More than 100,000 crash-relevant events are registered until today. As shown in Fig. 1, a front-view video with a duration of 15 seconds, the vehicle dynamics and location (GPS coordinates) as well as the driver operations are recorded by the drive-recorders mounted on more than 200 taxis throughout Japan. Some of the drive recorders also include driver face image capture for the analysis of driving behavior in detail. By using the drive recorders, information such as the velocity, the acceleration, the braking operation of drivers are acquired. [7] [8] [9]

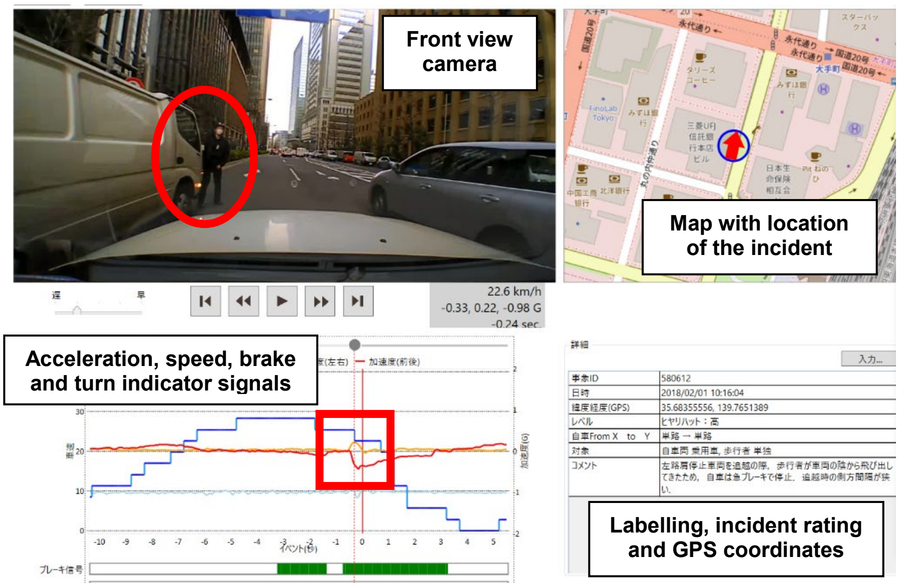

Fig. 1: User interface for manual labelling of incidents in the Near-Miss Incident Data Base

The registration of a potential incident, e.g. dashing out of the pedestrian behind the van marked with the red circle in Fig. 1, is automatically triggered. The devices mounted in the taxis record above mentioned data in a time frame of ten seconds before and five seconds after a combined acceleration value (vector of lateral and longitudinal acceleration) of the vehicle exceeds a threshold value of 3.5 m/s² (see red box in Fig. 1). This data is transmitted to a server and subsequently rating experts of TUAT append information about the driving context as well as manually rate the criticality of each incident. Moreover, by using image-processing technique, the distance to forward vehicles or objects like pedestrians can be estimated. Each potential incident will be categorized according to the level of criticality, the so-called the *Incident* Level. There are five possible values of the Incident Level: *Reaction, Low, Medium, High, Accident*.

B. Quantification of Driving Context Properties

The manually rated incidents of the Near-Miss Incident Data Base were analyzed regarding the influence of the human factors as well as the influence of different driving context properties on the criticality of the traffic situation. A total of 88 driving context parameters were investigated for such influence; the relevant parameters that influence the value of the Incident Level were quantified. Fig. 2 shows the quantified Risk Levels each property value of the context parameter *Intersection Type* in scenarios where the traffic opponent is a pedestrian as an example [10].

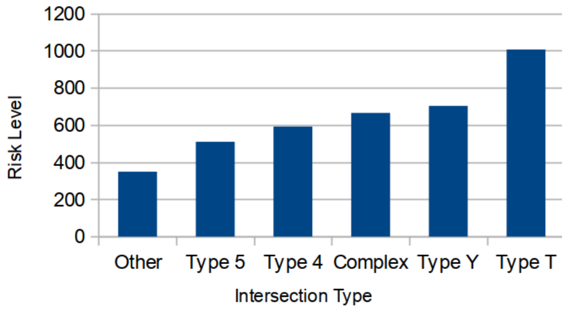

Fig. 2: Quantified Risk Levels of the property values of the context parameter *Intersection Type*

C. Safety Cushion Concept

Based on the quantified driver behavior (careful, thoughtful drivers vs. aggressive, careless drivers) and the driving context properties the concept of the *Safety Cushion* was developed (see Fig. 3). The Safety Cushion describes the additional braking distance that becomes available due to preventive driver actions who anticipate dangerous situations based on the evaluation of driving context parameters. The major difference to the well-known parameter *Time to Collision* is that the Safety Cushion describes an assumed braking distance to an anticipated obstacle. An adequate adjustment of the Safety Cushion decreases the number of necessary emergency brakes, i.e. number of critical situations in traffic, resulting in a strongly increased safety and driving comfort due to a smoother ride. [10]

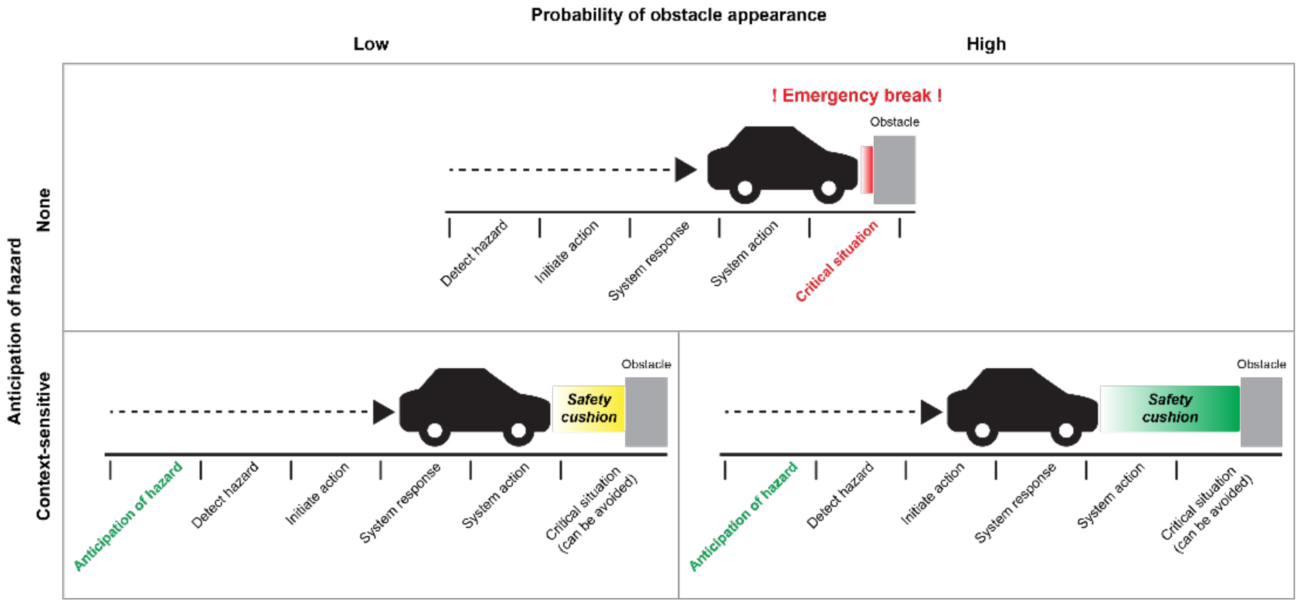

Fig. 3: Safe and comfortable ride by adjusting the Safety Cushion depending on the obstacle appearance probability

The adequate adjustment of the Safety Cushion can be achieved by evaluating the value of the parameter *Long-term Hazard Potential (LHP)* depending on the driving context. The LHP is based on the analysis of the driver behavior captured in the Near-Miss Incident Data Base. Its purpose is representing the hazard anticipation of experienced drivers that takes place in a time span a couple of seconds before the moment of potential incident (see Table 1). From the value of the LHP in different driving contexts it is possible to derive set values for the desired vehicle velocity resulting in a vehicle longitudinal acceleration in the same manner as careful drivers, reducing the potential hazard in the specific situation. It is assumed that the speed profile of experienced and careful drivers is an acceptable trade-off between driving comfort and safety [10] [11]. In this work, an autonomous driving algorithm concept based on the LHP will be used as application example to demonstrate the effectiveness of the proposed validation methodology and the utilized tools.

Table 1: Equation and parameters of the Long-term Hazard Potential (LHP)

Equation	Parameter	Parameter description
$LHP = \begin{cases} \dfrac{1 + v_{max} + \tilde{v} + \dot{v}}{1 + VAR(v)}, & \dot{v} > 0 \\ \dfrac{1 + v_{max} + \tilde{v}}{1 + VAR(v) + \dot{v}}, & \dot{v} \leq 0 \end{cases}$ (1)	v_{max}	Max. vehicle velocity in the interval t ϵ [-10 s, -3 s]
	$\tilde{v}$	Vehicle velocity median in the interval t ϵ [-10 s, -3 s]
	$\dot{v}$	Vehicle velocity gradient in the interval t ϵ [-5.5 s, -2.5 s]
	$VAR(v)$	Vehicle velocity variance in the interval t ϵ [-10 s, -3 s]

II. Setting Up the Virtual Environment and the System Under Test

A. Traffic Flow Simulation with PTV Vissim and Algorithm Implementation

PTV Vissim is an advanced traffic simulation software used to create accessibility, sustainability and a balanced mobility ecosystem in cities. Using PTV Vissim it is possible to model and simulate all operational interventions and assess their effect on the overall traffic flow. Furthermore, it offers the possibility to integrate customized models of single road users as custom integrable modules, Dynamic Link Library (DLL) and examine their interaction with other road users [12]. As shown in Fig. 4 marked with the red box this interface was used to integrate the LHP based autonomous driving algorithm.

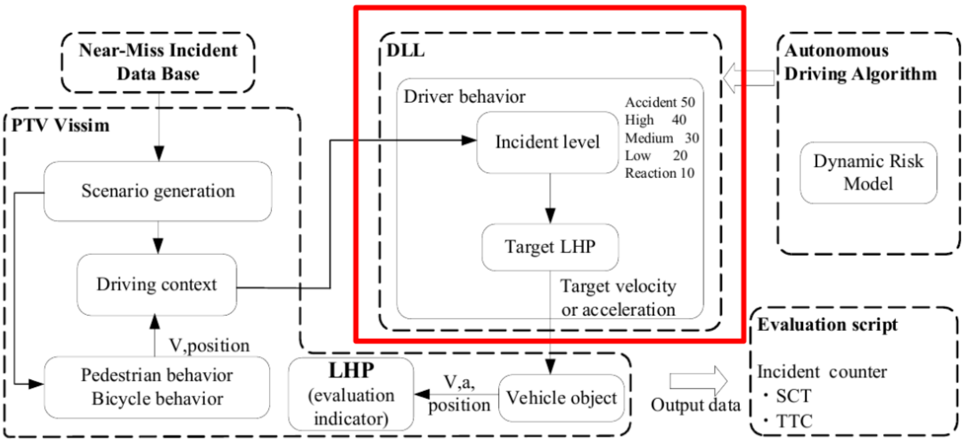

Fig. 4: Integration of new autonomous driving algorithms into the traffic simulation PTV Vissim and evaluation tools

B. Scenario Identification and Implementation in PTV Vissim

The proposed validation methodology focuses on the most critical possible scenarios that lead to the highest number of incidents or most critical incidents. These scenarios are based on real scenarios recorded in the Near-Miss Incident Data Base or synthetic scenarios constructed by combination of risky traffic and infrastructure parameters. Subsequently, the identified scenarios are classified regarding their context properties and especially regarding the behavior of the traffic opponents in order to generate clear requirements for the implementation of the simulation environment. Table 2 shows the six scenarios that are currently implemented in PTV Vissim and used for evaluating the new LHP-based autonomous driving algorithm which is based on human-like Dynamic Risk Management. As part of the future work, the number of critical scenarios implemented in PTV Vissim will be expanded, especially considering a deeper analysis of differences in traffic opponent behavior.

Different traffic opponent behavior is characterized by different movement patterns, i.e. different paths and speeds when approaching and crossing the potential conflict area. Fig. 5 shows the movement patterns for the traffic opponent behaviors modeled in this project. In the future, the traffic opponent behavior will be analyzed more in detail, in order to model it more precisely and obtain an even higher accuracy and realism of the simulated critical situations in traffic.

With the modeling environment of PTV Vissim it is possible to import data from geographical information sources and to construct real traffic networks. Fig. 6 shows the implementation of the scenario Bicycle – Curve in PTV Vissim. The relevant traffic opponent behaviors in this driving context are modeled by different routes; the distance between the beginning of the route where the traffic opponents appear, and the conflict area represents the time available for the vehicles to recognize the traffic opponent. This is illustrated in Fig. 6 by the relatively smaller distance of the route beginning for *Dash Out* in compare to *Straight Cross*.

Table 2: Scenarios implemented in PTV Vissim based on an analysis of the Near-Miss Incident Data Base

Scenario		**Infrastructure context**		**Traffic opponent behavior**	
Pedestrian	*Road*	Road: Construction:	Straight both ways 1	Head on Dash out Swing	1 % 95 % 4 %
	Intersection	Road Intersection: Traffic light: Crosswalk:	Straight both ways Type 4 2 2	Head on Swing Turn cross Dash out	18 % 44 % 23 % 16 %
	Curve	Curve: Road: Priority: Traffic light:	Obtuse Straight one way 1 1	Swing Head on Straight cross Dash out	5 % 23 % 40 % 32 %
Bicycle	*Road*	Road: Crosswalk:	Straight both ways 1	Swing Dash out Head on Straight cross	14 % 69 % 5 % 12 %
	Intersection	Intersection: Road: Traffic lights: Crosswalk: Stop line:	Type 4 Straight both ways 2 2 1-2	Turn cross Dash out Head on Straight cross	38 % 4 % 33 % 25%
	Curve	Curve: Road: Traffic light: Crosswalk:	Obtuse Both ways 1 1	Turn cross Head on Dash out Straight cross	31 % 22 % 9 % 37 %

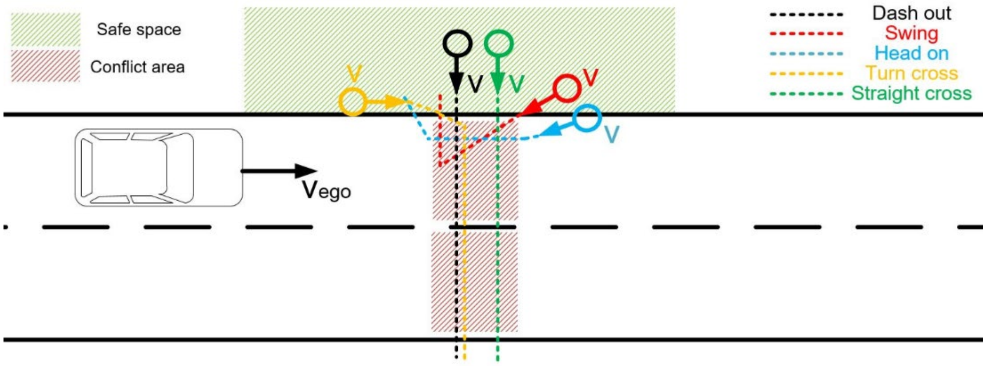

Fig. 5: Movement patterns of different traffic opponent behaviors implemented in PTV Vissim

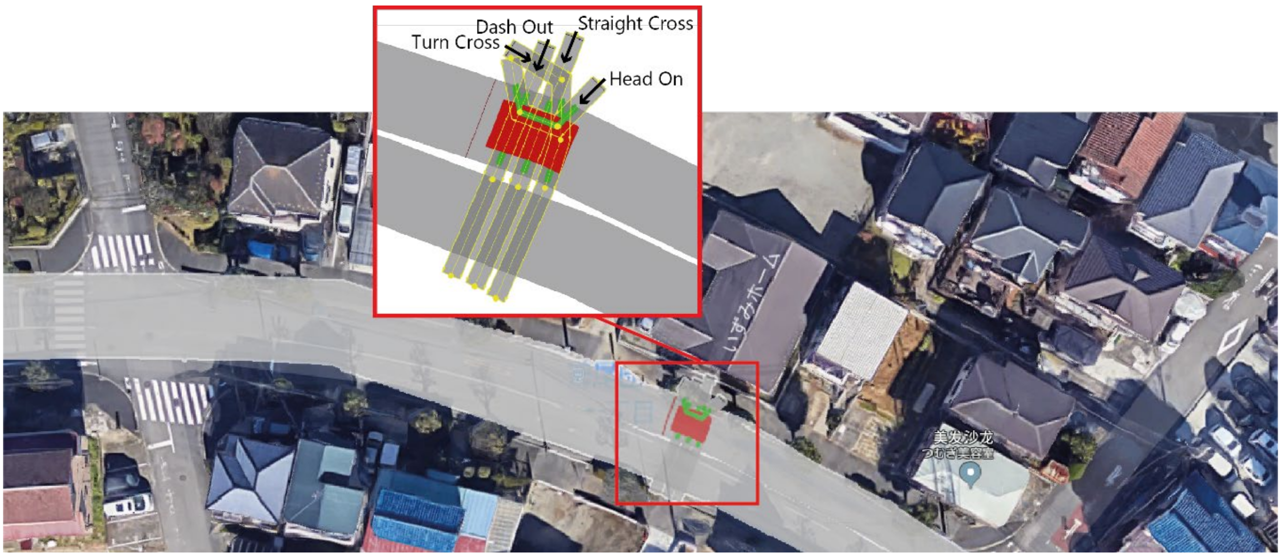

Fig. 6: Scenario *Bicycle – Curve* modelled in PTV Vissim

IV. Detection of Incidents in the Virtual Environment

One of the core elements of the proposed validation tool chain is the *Incident Detection Algorithm*. The purpose of this algorithm is to automatically evaluate situations in the virtual environment in the same way as the rating expert would do, when analyzing and manually rating incidents of the Near-Miss Incident Data Base. The algorithm combines the Safety Cushion concept with the *Point-in-Polygon (PIP)* algorithm; the latter is well known from motion planning, computer vision and other applications. The PIP simply answers the question if a given point lies inside or outside of a defined polygon.

For all vehicles and traffic opponents that are located on the relevant lane in the PTV Vissim traffic network, bounding boxes are calculated for each incident level in each simulation time step. The sizes of the bounding boxes are based on the Safety Cushion equation (see Table 3) with the respective Safety Cushion times for each incident level (High: SCT < 1 s, Medium SCT < 2 s: , Low: SCT < 3 s). With the PIP algorithm it is determined if overlapping bounding boxes of the vehicle and the pedestrian exist. In case there is an overlapping of bounding boxes of same incident level and the incident criteria apply (see Fig. 8), the incident is rated with the corresponding incident level. Fig. 7 shows three exemplary situations of the simulations conducted with PTV Vissim as well as the corresponding bounding boxes for the vehicle and the traffic opponent. In the first situation (A) the vehicle slowed down in a safe way and no incident occurred (no pedestrian bounding box in any vehicle bounding box). The second situation (B) shows an example of a low-level incident (low-level pedestrian bounding box in low-level vehicle bounding box). and the third situation (C) shows an example of a high-level incident (high-level pedestrian bounding box in high-level vehicle bounding box).

Table 3: Safety Cushion equation and parameters

Equation	Parameter	Parameter description
$$SCT(t) = \frac{D_{vehicle-opponent}(t) + \frac{v_{vehicle}^2(t)}{2a_{max}}}{v_{vehicle}(t)} - \tau \quad (2)$$	$SCT(t)$	Safety Cushion Time
	$D_{vehicle-opponent}(t)$	Distance between vehicle and opponent
	$v_{vehicle}(t)$	Vehicle velocity
	a_{max}	Max. braking acceleration
	τ	System reaction time

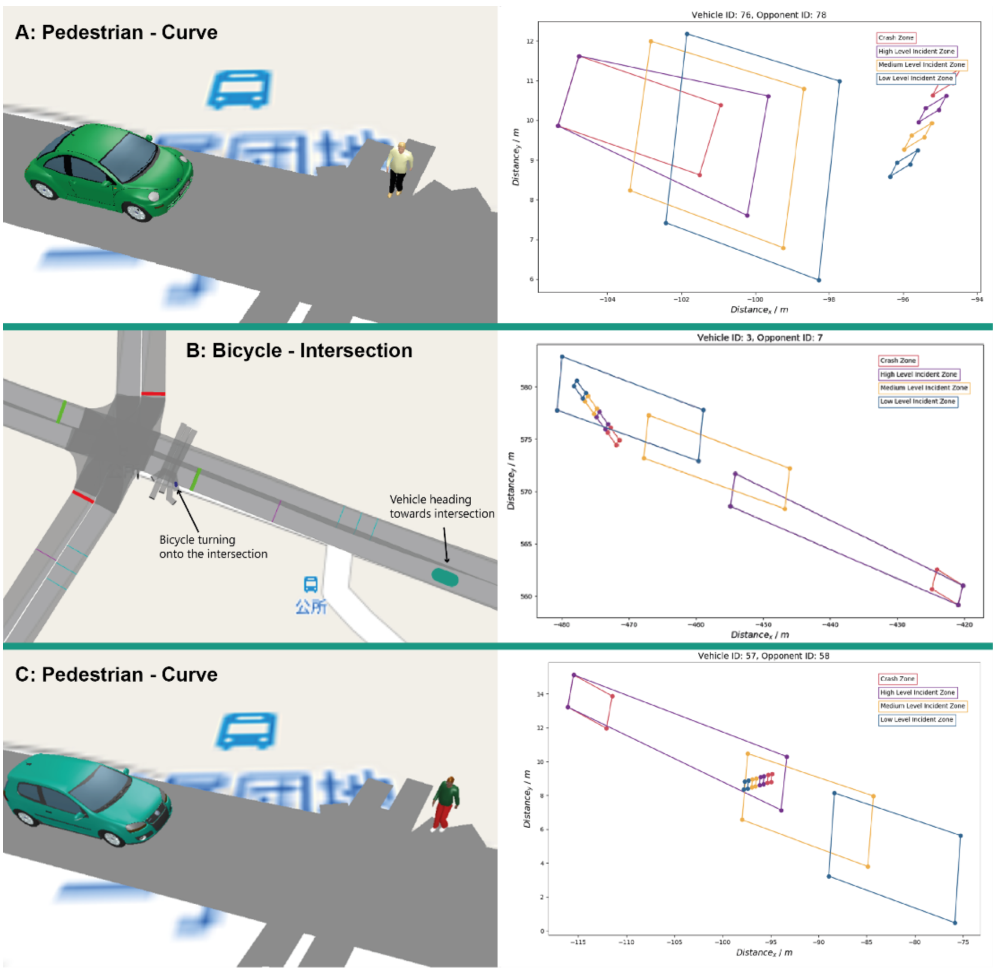

Fig. 7: Examples of critical situations during the simulation with PTV Vissim leading to different incident ratings

One of the main success factors of the incident detection algorithm is that it considers the same criteria as the rating experts. In doing so, it can be ensured that unrealistic driving behavior as well as situations that are not related to incidents (e.g. barking of cars due to traffic jams or normal breaking at traffic lights) are filtered out and not considered as relevant incidents between a vehicle and another road user. Fig. 8 shows the vehicle acceleration and the vehicle velocity over the simulation time. It can be seen that the vehicle reaction between simulation time 2822 s and 2824 s in combination with the appearance of a traffic opponent was not rated as incident (marked with dashed gray box in Fig. 8), whereas the events occurring between simulation time 2828 s and 2830 s were rated as medium level incident.

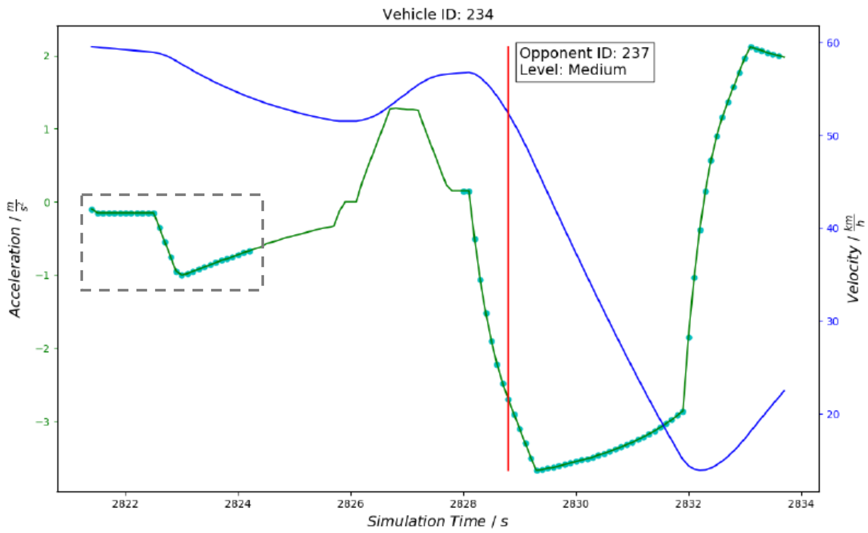

Fig. 8: Vehicle velocity and acceleration over simulation time at the moment of incident detection

V. Evaluation of the LHP-based Algorithm Performance

For obtaining a first approximation of the performance of the new autonomous driving algorithm a screening test plan was designed that varies the parameters listed in Table 4. This resulted in eight simulations for each traffic scenario described in Table 2, resulting in a total number of 48 simulations. The LHP-based algorithm was compared to the standard vehicle behavior implemented in PTV Vissim by comparing the number of crashes and the number of incidents in all traffic scenarios. As displayed in Fig. 9, the LHP-based algorithm reduced the total number of crashes as well as the total number of incidents in compare to the standard vehicle of PTV Vissim.

Table 4: Variation parameters of the screening test conducted with PTV Vissim for evaluating the LHP-based algorithm

Parameter	**Low value setting**	**High value setting**
Traffic intensity	100 vehicles / hour	200 vehicles / hour
Simulation time	1 day (86,400 s)	2 days (172,800 s)
Driving behavior of LHP-based algorithm	Defensive	Sportive

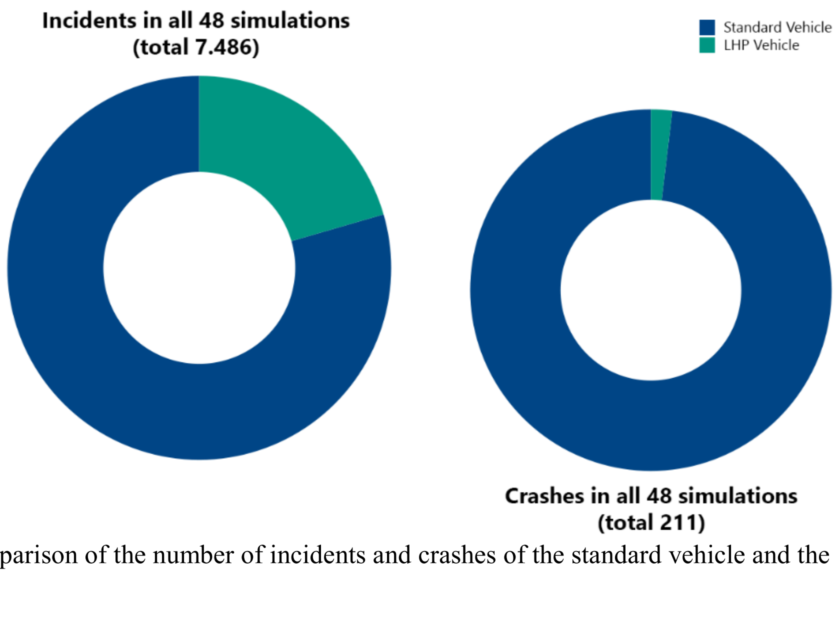

Fig. 9: Comparison of the number of incidents and crashes of the standard vehicle and the LHP vehicle

Fig. 10 displays for each traffic scenario the number of incidents, itemized by scenario and incident level. A major conclusion of the evaluation is that the LHP-based algorithm performs almost equally well in all scenarios. This conclusion is backed by analysis of the test results of the screening test with the EDI hive Model Generator (see Fig. 11 in comparison to Fig. 12). The reason for this is the context-sensitive adaptation of the Safety Cushion: In scenarios where a higher risk is predicted, the set speed of the vehicle with the LHP-based algorithm is lower than in scenarios with less predicted risk. However, in scenarios that feature a high percentage of Dash Out (e.g. Pedestrian – Road) the critical incidents are slightly higher than in scenarios that feature a low percentage of Dash Out (e.g. Bicycle – Intersection). This result can be traced back to the higher traffic opponent movement speed and the shorter line of visibility for the vehicles.

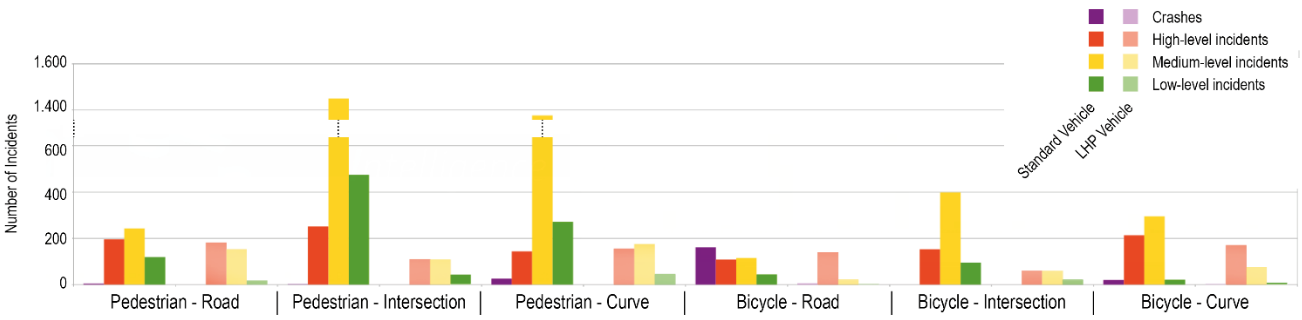

Fig. 10: Comparison of the number of incidents in all 48 simulations, itemized by scenario and incident level

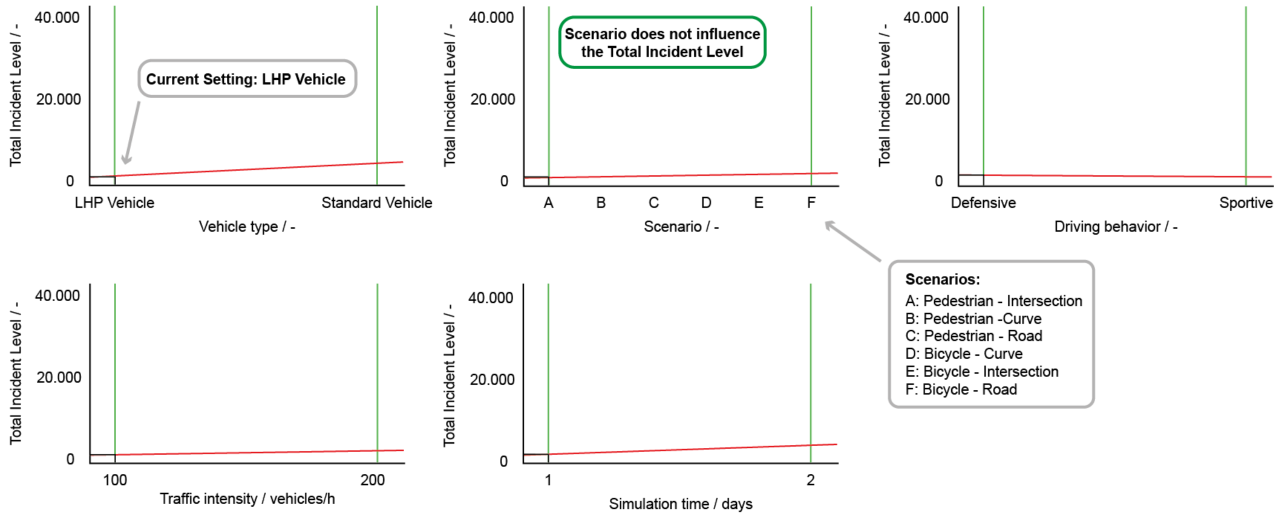

Fig. 11: Analysis of the screening test result with the EDI hive Model Generator (vehicle type: LHP Vehicle)

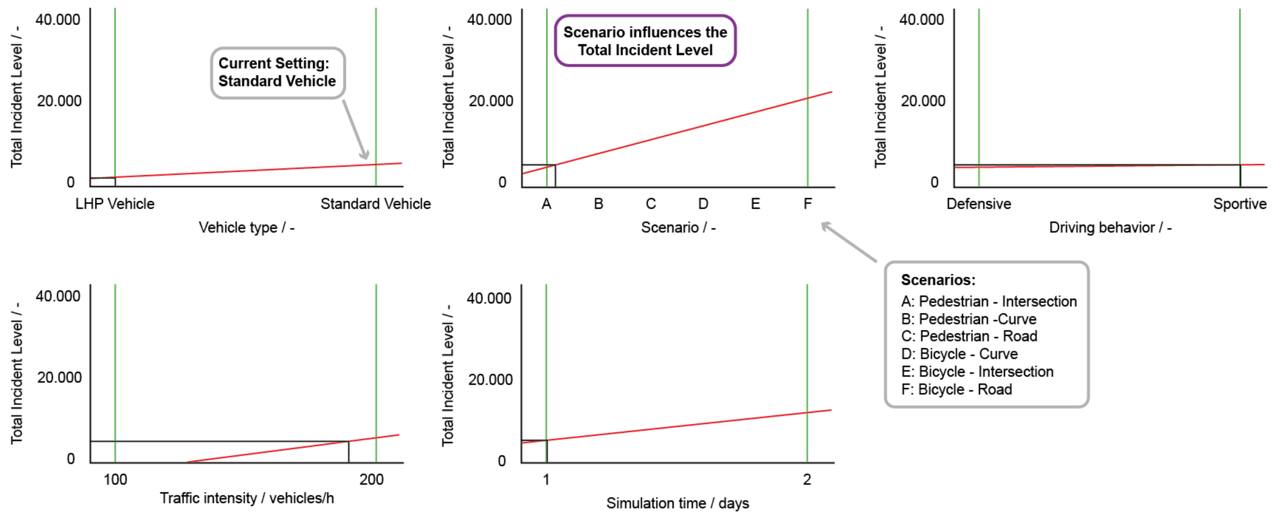

Fig. 12: Analysis of the screening test result with the EDI hive Model Generator (vehicle type: Standard Vehicle)

VI. Conclusion and Future Work

This paper introduced a framework for a virtual validation methodology with a corresponding tool chain for the evaluation of autonomous driving algorithms. The basis of this work is the Near-miss Incident Data Base which contains video data and vehicle measurement signals of more than 100.000 incidents in Japan. The central tool of the virtual validation environment is the traffic flow simulation software PTV Vissim. It could be shown how the real traffic data has been analyzed, processed and aggregated in order to build up the virtual environment for realistic simulation of critical situations in traffic. The application of this environment was demonstrated by evaluating the performance of an algorithm based on the Long-term Hazard Potential (LHP) that objectifies driving behavior. The LHP is used to realize the context-sensitive adjustment of the Safety Cushion. This leads to a safer, smoother and more comfortable ride, avoiding critical situations by hazard anticipation. The developed validation environment can be used to evaluate any other autonomous driving algorithm as well, by integrating it into PTV Vissim via the DLL interface.

Especially in early stages of product development this approach can deliver important insights for OEMs as well as suppliers that will lead to an increase of quality and savings of product costs, especially by reducing the number of road tests. Another area of application is the safe infrastructure design for autonomous vehicles. With the proposed methodology, the influence of infrastructure properties on the performance of autonomous vehicles can be analyzed in detail. Subsequently, safer designs for future road infrastructure can be determined in order to contribute to an overall safer road traffic, especially for pedestrians and bicycle riders.

The focus of future work will be the analysis of traffic opponent behavior in detail, i.e. the detailed characterization of variety in traffic opponent behavior regarding vectors of movement, movement patterns and speeds. Furthermore, it will be analyzed how these human factors differ depending on various properties of the traffic infrastructure. With this more precise classification of the traffic opponent behavior as well as infrastructure geometry influences on the level of hazard in traffic more realistic and relevant traffic scenarios can be modeled and the quality of the simulation results will increase. The aim is to provide an extensive catalogue of relevant traffic scenarios for the validation of autonomous vehicles.

References

[1] S. Calvert et al., "Traffic Flow of Connected and Automated Vehicles: Challenges and Opportunities," in *Road Vehicle Automation 4. Lecture Notes in Mobility*, Meyer G., Beiker S, Springer, 2018.

[2] "From Driver Assistance Systems to Automated Driving," VDA - German Association of the Automotive Industry, 2015.

[3] "Global Status Report on Road Safety," World Health Organization, 2015.

[4] "A perfect sensor alone does not make a perfect system," IPG Automotive GmbH, 2017.

[5] R. Hussain and S. Zeadally, "Autonomous Cars: Research Results, Issues, and Future Challenges," IEEE, 2019.

[6] K. Philip and M. Wagner, "Challenges in Autonomous Vehicle Testing and Validation," SAE International, 2016.

[7] P. Raksincharoensak, D. Hasegawa, I. Iwasawa and Y. Michitsuji, "Hazard-Anticipatory Driver Modeling for Preventing Pedestrian Collisions in Unsignalized Intersections," JSAE, 2012.

[8] P. Raksincharoensak, K. Moro and M. Nagai, "Reconstruction of Pedestrian/Cyclist Crash-Relevant Scenario and Assessment of Collision Avoidance System Using Driving Simulator," AVEC, 2012.

[9] R. Matsumi, P. Raksincharoensak and M. Nagai, "Study on Autonomous Intelligent Drive System Based on Potential Field with Hazard," Journal of Robotics and Mechatronics (JRM 27), 2015.

[10] P. Raksincharoensak and H. Inoue, "Safety Cushion: Context-Sensitive Hazard Anticipation," in *FAST-zero 2017*, 2017.

[11] Y. Saito, P. Raksincharoensak, H. Inoue, M. El-Haji and F. Freudenmann, "Context-Sensitive Hazard Anticipation Based on Driver Behavior Analysis and Cause-and-Effect Chain Study," in *AVEC 2018*, 2018.

[12] "PTV Group," [Online]. Available: http://vision-traffic.ptvgroup.com/en-us/products/ptv-vissim/. [Accessed 27 6 2016].