THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Safety Evaluation Using Counterfactual Simulations

The use of computational driver behavior models in crash avoidance systems and virtual simulations with optimal subsampling

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Gothenburg, Sweden 2023

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Technical report no 2023:04

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Cover:
Illustration of the use of computational driver behavior models in crash avoidance systems and virtual simulations with optimal subsampling

Printed by Chalmers digitaltryck

Gothenburg, Sweden 2023

Abstract

Traffic safety is a problem worldwide. In-vehicle conflict and crash avoidance systems have been under development and assessment for some time, as integral parts of Advanced Driver Assistance Systems (ADAS) and Automated Driving Systems (ADS). Among the methods used to assess conflict and crash avoidance systems developed by the automotive industry, virtual safety assessment methods have been shown to have great potential and efficiency. In fact, scenario generation-based virtual safety assessments play—and are likely to continue to play—a very important role in the assessments of vehicles of all levels of automation. The ultimate aim of this thesis is to improve the safety performance of conflict and crash avoidance systems. This aim is addressed through the use of computational driver models in two different ways. First, by using comfort-zone boundaries in system design, and second, by using a behavior-based crash-causation model together with a novel optimized scenario generation method for virtual safety assessment.

The first objective of this thesis is to investigate how a driver model which includes road users' comfortable behaviors in crash avoidance algorithms impacts the systems' safety performance and the residual crash characteristics. Chinese car-to-two-wheeler crashes were targeted; Automated Emergency Braking (AEB) algorithms, which comprised the proposed crash avoidance systems, were compared to a traditional AEB algorithm. The proposed algorithms showed larger safety performance benefits. In addition, the similarities in residual crash characteristics regarding impact speed and location after different AEB implementations can potentially simplify the designs of in-crash protection system in future.

The second objective is to develop and apply a method for efficient subsampling in crash-causation-model-based scenario generation for virtual safety assessment. The method, which is machine-learning-assisted, actively and iteratively updates the sampling probability based on new simulation results. The crash-causation model is based on off-road glances and a distribution of driver maximum decelerations in critical situations. A simple time-to-collision-based AEB algorithm was used to demonstrate the assessment process as well as the benefits of combining crash-causation-model-based scenario generation and optimal subsampling. The sampling methods are designed to target specific safety benefit indicators, such as impact speed reduction and crash avoidance rate. The results of the study show that the proposed sampling method requires almost 50% fewer simulations than traditional importance sampling.

Future work aims to focus on applying the active sampling method to driver-model-based car-to-vulnerable road user (VRU) scenario generation. In addition to assessing conflict and crash avoidance system performance, a novel stopping criterion based on Bayesian future prediction will be further developed and demonstrated for use in experiments (e.g., as part of developing driver models) and virtual simulations (e.g., using driver-behavior-based crash-causation models). This criterion will be able to indicate when studies are unlikely to yield actionable results within the budget available, facilitating the decision to discontinue them while they are being run.

Keywords: Advanced Driver Assistance Systems, Automated Driving Systems, counterfactual simulation, scenario generation, safety assessment, active sampling, car-to-VRU, conflict and crash avoidance

Acknowledgements

I want to express my sincere gratitude to my supervisor Jonas Bärgman and co-supervisor Carol Flannagan for their invaluable guidance, support, and encouragement throughout my studies. I would also like to thank András Bálint for his support and supervision during the first two years, and to my examiner Marco Dozza for all the insightful discussions and meetings. I would like to thank all my colleagues at the division for the stimulating discussions, enjoyable fika, lunch, and after-work time with all of you.

I am indebted to my family for their endless support and understanding during my studies and I feel very fortunate to be a part of such a loving and supportive family. I am grateful to Eric for his unwavering love, kindness, and support, which have been a source of strength and comfort to me throughout our time together. I would like to thank Lotta, Peter, and Emelie for treating me like a family member and creating a warm atmosphere, making me feel at home.

I would like to thank friends and colleagues I have met during and outside of projects. Thanks Simon, Malin, and Erik for their support and encouragement during and outside of the HAM project. Thanks Wudi and Shuyu for all their support during my downtime.

I acknowledge the SHAPE-IT project, which supported the research work under the European Union's Horizon 2020 research and innovation programme (under the Marie Skłodowska-Curie grant agreement 860410).

Contents

1 Introduction

Approximately 1.3 million people die annually in road traffic worldwide, and more than half of the deaths are among vulnerable road users (VRUs), a category including pedestrians and all two-wheeler (TW) riders (World Health Organization, 2018). Car-to-TW crashes are problematic in many countries, especially in China where the number of powered two-wheelers (PTWs) has rapidly increased from 2013 to 2018 (National Bureau of Statistics of China, 2019; Strandroth, 2015; World Health Organization, 2017). In 2018, 10,663 motorcyclists died and 55,071 were injured in traffic in China (National Bureau of Satistics of China, 2019). Due to the substantial negative impact on society, many researchers have studied crashes and crash mechanisms in order to identify the problems that need to be solved (Bianchi Piccinini et al., 2017; Bucsuházy et al., 2020; Petridou & Moustaki, 2000; Viano & Ridella, 1996; Xuesong Wang et al., 2022). Human factors contribute to as much as 94% of all traffic crashes (NHTSA, 2015). Therefore, many argue that the number of traffic safety situations involving fatalities and injuries will be reduced substantially with the development of Advanced Driver Assistance Systems (ADAS) and Automated Driving Systems (ADS) (Cicchino, 2016; Jermakian, 2011; Kyriakidis et al., 2015; Payre et al., 2014; Rödel et al., 2014). In fact, ADAS has already been shown to substantially improve traffic safety (Cicchino, 2016, 2017; Fildes et al., 2015), while data on ADS are only starting to come in. Conflict and crash avoidance are integral parts of both ADAS and ADS. Conflict avoidance refers to the vehicles' ability to avoid conflicts in everyday driving even as the traffic environment changes dynamically. Crash avoidance, on the other hand, refers to the vehicle's ability to avoid a crash (or mitigate its consequences) in a critical situation, when a crash is imminent if an avoidance maneuver is not initiated (Jermakian, 2011). To ensure that conflict and crash avoidance systems improve safety, they need to be assessed as part of their development process (Jeong & Oh, 2017; Lemmen et al., 2012; Lindman & Tivesten, 2006; Zhao et al., 2017). In addition, regulatory constraints (ISO, 2019, 2021a, 2021b, 2022), and consumer testing programs (C-NCAP, 2018, 2020; Euro NCAP, 2022, 2023) also require methods to assess safety.

1.1 Conflict and crash avoidance systems

Conflict and crash avoidance are integral parts of both ADAS and ADS; to understand and study conflict and crash avoidance systems, ADAS and ADS should be defined in more detail, given that there is still some confusion about their differences. They represent different levels of automation (as defined by the 2021 SAE). ADAS are advanced technologies which assist drivers during driving tasks by providing information, warnings, and/or interventions related to events unfolding, by taking over part of the driving, or by supporting the driver. The most popular ADAS include warning systems like lane departure warning (LDW) (Son et al., 2015) and forward collision warning (FCW) (Dagan et al., 2004), and automated systems like automated emergency braking (AEB) (Haus et al., 2019), adaptive cruise control (ACC) (Benmimoun et al., 2013), and lane keeping and centering (Tsoi et al., 2010). FCW, AEB and ACC are longitudinal control systems, while LDW, lane keeping, and centering are lateral control systems.

In contrast to ADAS, ADS aim to relieve drivers of the driving task by taking over entirely—at least for part of the drive (i.e., conditional automation; SAE, 2021). Examples already on the market today include the autonomous vehicles produced by Waymo (Scanlon et al., 2021; Waymo, 2022), 'autonomous cars' with no drivers which transport paying customers; and by Daimler (Daimler, 2020), which produces the first vehicles approved for conditional

automation in Europe (with a driver behind the steering wheel). Furthermore, there are several vehicles on the market that are on the upper end of the ADAS level of automation, but where driver supervision of the vehicle's automated driving task is still needed. That is, drivers' reaction and response times to both the road situations and the safety systems influence road safety. Examples of such systems are vehicles from Tesla (Ingle & Phute, 2016; Tesla, 2022), who are branding their vehicles as self-driving or even fully self-driving, but still require that the driver to be attentive and in control: the driver is still responsible. Actually, a recent report from the Insurance Institute for Highway Safety (IIHS) in the US (Matt, 2022), report that 53% of General Motors' Super Cruise users and 42% of Tesla Autopilot users were comfortable not paying attention to the roadway while the vehicles drove—although the users are still ultimately responsible.

Human factors play an important role in automation development; therefore, understanding and adopting driver behaviors is often essential for developing conflict and crash avoidance systems. Generally, drivers' perceived safety, feeling of comfort, and level of trust in the systems impact their acceptance and use of new or developing systems (J. D. Lee & See, 2004; Molnar et al., 2018; T. Zhang et al., 2020). Some researchers have conducted experiments on drivers' feelings about different automated driving algorithms. For example, Peng et al. (2022) showed that automated driving algorithms which include human driver behaviors were rated higher in comfort by the participants. This is only one consideration about the inclusion of driver behaviors in the system designs for developers of conflict and crash avoidance system to keep in mind.

Driver behavior models have been used in different ways in the development of conflict and crash avoidance systems. For example, some driver models, such as reaction times to forward collision warnings (T. L. Brown et al., 2001) and driver response times for ACC (Higashimata et al., 2001), can be directly included in system designs. Another use is as reference driver models in safety assurance and safety argumentation of conflict and crash avoidance systems, which represent highly performant drivers (from a safety perspective). One example is Waymo's NIEON ("Non-Impaired, with Eyes ON the conflict"), a reference driver model that represents "consistently performing, always-attentive drivers" (Scanlon et al., 2022). However, including driver models explicitly in system designs and assessments is still relatively rare. For example, effective crash avoidance systems like AEB, which brake at the last moment to avoid or mitigate crashes, typically do not include driver behaviors in the algorithm design in published work—with some exceptions (Brännström et al., 2010; Sander, 2018).

Traditional AEB systems are often based on time-to-collision (TTC) (Kusano & Gabler, 2012) or required deceleration (Brännström et al., 2010; Coelingh et al., 2007). TTC-based AEB usually triggers when the vehicle reaches a fixed TTC threshold, while required-deceleration-based AEB takes the maximum braking level of a vehicle into consideration and aims to trigger at (or just before) that point of no return—after which the vehicle cannot possibly brake to avoid the crash. There have been many studies on the real-world effect of AEB (e.g., Fildes et al., 2015; Haus et al., 2019); although it improves safety substantially, it has the potential to improve safety even more. Many crashes would have been avoided if AEB had been triggered earlier. The problem is, of course, that triggering earlier may substantially increase nuisance interventions, which can be both irritating and dangerous. There are alternatives to the traditional AEB algorithms that instead take driver comfort into account, enabling AEB to trigger earlier without being a nuisance.

Drivers' comfort zone boundaries (CZBs) define drivers' comfortable braking and steering limits. CZB are typically quantified based on naturalistic studies (Dingus et al., 2006) and controlled experiments (Bärgman, Smith, et al., 2015). While there are a few studies that do consider drivers' CZBs in car-to-car AEB system algorithms (e.g., Sander, 2018), that is not the case for car-to-TW algorithms. However, TWs are becoming more prevalent on public roads, especially in developing countries like China (National Bureau of Statistics of China, 2019). Powered two- or three-wheelers were involved in nearly 30% of crash fatalities reported in 2016 worldwide (World Health Organization, 2017); thus it is very important to develop conflict and crash avoidance systems to avoid such crashes and improve VRU safety. However, although AEB studies have estimated its benefit in car-to-car (Fildes et al., 2015) and car-to-pedestrian scenarios (Cicchino, 2022; Rosén, 2013), few have studied car-to-PTWs (Sui et al., 2021), not to mention CZB-based car-to-TW AEBs. Therefore, there is a need to investigate the crash-avoidance benefits of CZB-based TW AEB through, for example, virtual simulations (Paper I).

1.2 Virtual simulations for safety benefit assessment

Counterfactual simulations and traffic simulations are the two main virtual simulation approaches for assessing different aspects of traffic. Counterfactual simulations have been used primarily to quantify the performance of safety systems (Cicchino, 2022; Haus et al., 2019; Rosén, 2013; Sander, 2018; Scanlon et al., 2022), while traffic simulations have traditionally been used to evaluate traffic flow control, roadway design, and vehicle systems, which could influence road-user behaviors and vehicle performance (Archer, 2005; Vrbanić et al., 2021). A key difference between the two approaches is that counterfactual simulations use at least some kinematics data from actual conflicts directly in the simulations while traffic simulations rely on driver models, traffic models, interaction models, and traffic situation setups (Archer, 2005; Krajzewicz, 2010). Even though some research has shown that it is possible to generate, to some extent, realistic safety-critical events using traffic simulations without making unnecessary and unrealistic behavioral assumptions (Archer, 2005; Bieker-Walz et al., 2018), the reliability and accuracy of traffic simulation are still highly dependent on model fidelity and data quality (Krajzewicz, 2010).

What is special about counterfactual simulations is that they enact what would have happened if there, in a specific event, had been conflict and/or crash avoidance systems (typically an ADAS or part of an ADS) before the crashes happened. Performing simulations requires kinematic data of the pre-crash phase, such as measurements of real-world crashes from event data recorders (Gabler et al., 2004) or from in-depth studies of individual crashes (Sander & Lubbe, 2018), for example. Sources for these data include the German In-Depth Accident Study (GIDAS) pre-crash matrix (PCM; Rosén, 2013; L. Stark et al., 2019), China In-Depth Accident Study (CIDAS) PCM (T. Wei et al., 2022), and China Shanghai United Road Traffic Safety Scientific Research Center pre-crash time-series data (SHUFO PCTSD) (Sui et al., 2021). Pre-crash kinematics data commonly capture dynamic information such as traffic participants' velocities, accelerations, positions, heading angles, etc., for several seconds before the crashes. In the simulation, the system could intervene and change the dynamics of vehicles in the scenarios, which could lead to avoiding the crash or mitigating its severity. The important metrics for safety assessment are those that explicitly evaluate the benefits of a system, such as crash avoidance rate, impact speed reduction, and injury mitigation.

1.3 Scenario generation

Scenario generation is the creation of scenarios for use in virtual safety assessment. In counterfactual simulations, the original crash kinematics without the safety system are usually

(at least to date) obtained from measured or reconstructed manual driving situations—often from in-depth crash databases. The data are used as baseline scenarios; when the safety system is (virtually) applied to these scenarios, they become treatment scenarios. However, conflict situations collected in traffic are rare, and data from crash reconstructions are even rarer, so their statistical power is typically low. It is thus highly beneficial to generate (create) conflict situations (not the least crashes) which are representative of the scenario under study. This process, typically called scenario generation, is shown in Figure 1. Scenario generation is a commonly used virtual simulation method for safety verification and validation of conflict and crash avoidance systems (Amersbach & Winner, 2019; Åsljung et al., 2017; Beglerovic et al., 2017), as well as for their safety benefit assessment (De Gelder & Paardekooper, 2017; Junietz et al., 2019). The scenario generation approach is popular and well investigated and has been developed and used in many projects, including L3Pilot (Bjorvatn et al., 2021), V4SAFETY (European Commission, 2022), and PEGASUS (Winner et al., 2019). Safety benefit assessment is at the core of both papers in this thesis, focusing on the quantification of the safety benefit of a specific conflict or crash avoidance system, typically in terms of crash avoidance rate, impact speed reduction, and injury risk reduction.

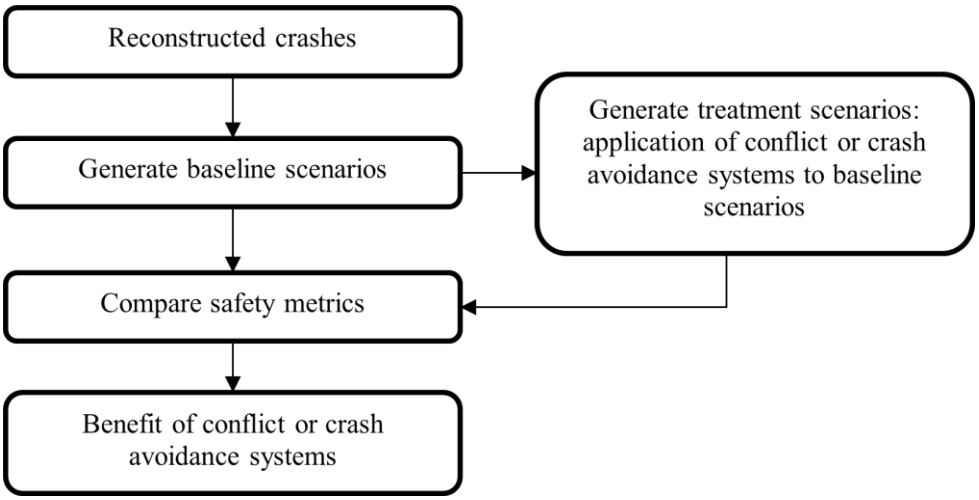

Figure 1: The illustration of scenario generation using counterfactual simulation for conflict or crash avoidance system assessment

Scenarios can be divided into three different categories based on the level of detail: functional, logical, and concrete (Menzel et al., 2018). Among the three scenario categories, concrete scenarios are commonly used for safety assessment as they are the most detailed, requiring defined parameter values. For example, reconstructed crashes are concrete scenarios.

Concrete scenarios can be extracted and generated directly by machine learning methods; some of these methods can detect and identify existing data characteristics and generate new concrete scenarios based on those characteristics without the need for grouping or sampling. For example, generative neural networks were used by Krajewski et al. (2018) to generate new lane-change trajectories based on trajectories of recorded maneuvers. Their results showed that the generated trajectories were realistic. Another way to generate concrete scenarios is to first create logical scenarios defined by parameter ranges or distributions (Menzel et al., 2018). New concrete scenarios can then be generated based on the logical scenarios using some sampling method.

Machine-learning methods can also be used to create logical scenarios either by unsupervised clustering or supervised classification. For example, Kruber et al. (2018) used unsupervised clustering methods to group measurement data into different clusters (logical scenarios) and Beglerovic et al. (2018) used an end-to-end Deep Learning approach to classify logical scenarios from real driving data for a lane-keeping assist system. Rule-based methods can also be used to identify logical scenarios. Rule-based methods are different from machine-learning methods, which commonly cluster or classify some logical scenario(s) with parameters of road participants' dynamics (e.g., initial speed) and the road network (e.g., lanes). The rule-based methods, on the other hand, define logical scenarios with constraints or rules together with data source, and parameterize the scenarios with model or scenario parameters. Depending on the specific approach, the parameters may be driver braking level and glances on/off road, or the parameters may be purely kinematical and other scenario characterization parameterizations (e.g., speeds and decelerations of involved vehicles, and light or road conditions). Crash causation-based scenario generation is one such rule-based method, which incorporates crash causation mechanisms into the simulations to mimic crashes in the real world by capturing why crashes happen. Since human error contributes to as many as 94% of crashes, driver models which represent driver behaviors, including those related to driving and attention, should thus be considered when developing crash causation models for scenario generation. The driver models may contain parameters to represent driver responses (e.g., braking or steering) and the state of attention (e.g., whether the driver is looking on/off road) in critical situations. Paper II in this thesis uses such a crash-causation-model-based scenario generation approach.

The generated logical scenarios based on either machine-learning or rule-based methods can be captured by parameter ranges or parameter distributions. However, if they contain ranges (rather than distributions from real data), the generated scenarios only represent the scenarios covered, without information about their exposure (e.g., the probability of the individual concrete scenario occurring in the real world) (Cai et al., 2022; Nalic et al., 2020; Riedmaier et al., 2020). Conversely, scenarios generated by sampling from distributions can—at least in theory—provide exposure data, enabling safety benefit estimations that quantify the safety impact (e.g., estimations of crash avoidance rate, impact speed reduction, and injury risk reduction).

The two sampling approaches address two very different questions. Scenario generation that does not provide (hopefully realistic) estimates of exposure is typically used in system validation and verification (Khastgir et al., 2017), where you need to show that the system performs as expected, not make an estimation of the safety benefits. Although both approaches can be part of safety assurance and argumentation, exposure must be a part of scenario generation if the scenarios are to be used for virtual safety assessments that aim to quantify the safety impact (e.g., crash avoidance rate, impact speed reduction, and injury risk). Thus only applications considering exposure are considered in this thesis. The quantification of safety impact will hereafter be called safety benefit assessment. Also note that the data from which distributions come (in exposure-considering scenario generation) must be relevant, and joint distributions are often needed, as parameters are often correlated (J. Kim & Mahmassani, 2011). In summary, concrete scenarios can be generated from logical scenarios by combining distributions of specific parameters—either parameters describing direct interaction dynamics or parameters of the driver models that are used in the simulation to generate scenarios— but to quantify the impact it has on safety, the distributions must be accurate enough and relevant for the real-world crashes to be generated.

As scenarios and models become more complex and the number of parameters increase correspondingly, it is intractable to run all combinations of all parameters because of finite time and computational resources. Sampling methods can be used that allow a selected subset of all combinations of parameters to represent the whole population mean, distribution, or quantiles. These subsampling methods are widely used in the medicine domain (Huijben et al., 2020). Most literature on scenario generation has used importance sampling methods (De Gelder & Paardekooper, 2017; O'Kelly et al., 2018; Xinpeng Wang et al., 2021). However, importance sampling has a fixed sampling scheme and requires prior knowledge to set the sampling scheme, which can be a substantial problem when the prior knowledge is unknown or wrong. Paper II in this thesis proposes a novel way to perform importance sampling.

1.4 Aims and objectives

The overarching aim of this research is to improve the safety performance of conflict and crash avoidance systems by using computational driver models through a) the development of improved crash avoidance systems based on driver comfort-zone-boundary-based algorithms and b) improving safety performance assessment methods that use driver behavior models by developing and applying efficient sampling methods. Specifically, the aim of this licentiate work is to investigate the use of computational driver models in crash avoidance systems and scenario generation while developing optimal subsampling methods for more precise and efficient virtual safety assessment. In order to achieve this aim, this licentiate has two objectives:

- to investigate how the inclusion of a driver behavior model in crash avoidance algorithms targeting car-to-PTW crashes impacts the systems' performance and residual crash characteristics.
- to develop and apply a method for efficient subsampling for use with a driver behavior-based crash causation model in scenario generation.

The research after the licentiate will seek to continue to improve safety assessment methods through the use of computational driver-behavior models in three ways: a) further investigating the practicalities of applying the efficient subsampling method in crash-causation-model-based scenario generation, b) extending the crash-causation-model-based scenario generation to car-to-VRU crashes, and c) continuing research on how to perform sequential decision making for more efficient execution of driver behavior studies modeling driver behaviors. As the research in c) is already underway, a short background and problem formulation are provided.

2 Data, models and simulations

This chapter briefly introduces the data used for virtual safety assessment in general, as well as the data used specifically in this work. It also briefly describes some uses of road-user models in virtual safety assessment in general in Section 2.2, as well as their application in this work. Next, Section 2.3 introduces sampling methods used in virtual safety assessment with the focus on the sampling method applied in this work.

2.1 Data for virtual safety assessment

Different types of data can be used as the basis for virtual safety assessment and in the development of components (e.g., models of driver behavior) which can be part of virtual safety assessment. For example, crash data can be used directly as the baseline scenarios, and in most cases the reconstructed pre-crash kinematics data from crashes are used in counterfactual simulations. The crash datasets can be region-based, like US data (Kusano & Gabler, 2014), German data (L. Stark et al., 2019), Chinese data (T. Wei et al., 2022), or Indian data (Pisharam et al., 2022). Pre-crash kinematics can also be used as a basis for generating scenarios for use in the assessment of conflict and crash avoidance systems (Esenturk et al., 2021; Song et al., 2022; C. Stark et al., 2020). Bärgman et al. removed driver braking behaviors in original rear-end crashes, and used the modified data with an added driver model (to represent drivers' braking behavior and crash-causation mechanisms) to generate more crashes. Different data sources can also be combined to generate critical baseline scenarios to estimate the safety benefits with a certain system. For example, Waymo (Scanlon et al., 2022) combined collected real-world crash and near-crash data, ADS testing data, and expert knowledge in their process for identifying critical scenarios for the safety verification and validation of ADS.

Data from multiple sources other than crashes, including naturalistic driving data, test-track data, simulator experiment data, and near-crash data, are also often used in the development of components for safety assessment. One such component is a driver model, which can represent driver behaviors in certain driving scenarios. Driver models have been developed for cut-in scenarios (S. Kim et al., 2017), overtaking scenarios (Farah et al., 2019), rear-end crash scenarios (Markkula et al., 2012). Driver distraction models have also been developed for secondary-task scenarios (Ersal et al., 2010). Driver behavior is not the only behavior that can be modeled. The behavior of other road users, like pedestrians and TWs, can also be modeled, given an appropriate data source. As one example, Yi et al. (2016) used naturalistic data to train a deep neural network to model pedestrian behaviors in crowded scenes. Another example is pedestrian trajectory prediction in urban traffic scenarios, which uses a developed neural network (C. Zhang et al., 2021). The network does not create a model that independently describes pedestrian motion; rather, the model attempts to predict it. The model's primary usefulness is inside a system (e.g., an ADS). It is important to note that different types of road user behavior models are needed for different purposes, and the different models and model types require different data.

When a model has been developed and integrated into some specific conflict or crash avoidance system, data are needed to assess the system's safety performance. Dozza et al. (2020) developed a "smart collision avoidance system" for overtaking cyclist scenarios, which was assessed using test-track data to identify false negatives (i.e., verifying that the system did not miss a warning in a critical situation) and field data to identify false positives (i.e., verifying that the system did not give a warning unnecessarily). Another example of the use of data for assessing a developed system's performance is the work of Keller & Gavrila

(2014). They investigated four approaches for stereo-vision-based pedestrian path prediction and used field testing experiment data to assess the performance of the four approaches. Naturalistic driving data can also be used to assess the usage of different driver models for the reliable estimation of safety assessment, such as in the work of Kovaceva et al. (2022).

Different data types, including reconstructed crash data, naturalistic data, and test-track data, were used in this study. For example, 93 SHUFO PCTSD car-to-PTW crashes (Paper I) and 44 Volvo rear-end crashes (Paper II) were used. SHUFO PCTSD consists of reconstructed pre-crash kinematics data based on the SHUFO crash database. The SHUFO crash database mainly consists of real crashes collected in the Shanghai Jiading distinct in China; the selection criteria are at least one passenger car involved, at least one airbag deployed, at least one severe-level injury, or at least US$3500 economic loss (Deng et al., 2013). The Volvo rear-end crash data used were selected from an internal Volvo crash dataset, with the main selection criteria being that the cost of the crash exceed €4500 (Isaksson-Hellman & Norin, 2005). The SHUFO PCTSD has a structure similar to that of the GIDAS PCM (Sui et al., 2021). The data contain detailed (reconstructed) kinematics information for a few seconds before the crashes happened, which can be used for counterfactual assessment. In this study, SHUFO PCTSD were used for the performance assessment of different AEB systems targeting car-to-TW crashes in China. Naturalistic and test-track data were also used in the studies performed as part of this thesis: the CZB thresholds used in Paper I are based on naturalistic and test-track data, and the glance and maximum deceleration data used in Paper II were also extracted from naturalistic data.

2.2 Road-user behavior models

This section first introduces different road-user behavior models in system designs in general, followed by our specific application in Subsection 2.2.1. Subsection 2.2.2 introduces the usage of road-user behavior models in virtual safety assessment in general and in our scenario generation application. The choice of driver model matters substantially for system assessment and performance.

2.2.1 Driver behavior models as a part of vehicle system algorithms

We do not know exactly what algorithms are in the safety system of production vehicles (as car manufacturers typically do not disclose that information), so we do not know if the algorithms include road-user behavior models such as CZBs in their design. However, some literature has reported on studies of CZB safety systems, which are based on behavior rather than purely on possible physical avoidance. For example, a driver model was used in the crash avoidance system design presented by Dozza et al. (2020). They first designed the crash avoidance system to issue a warning if there was a mismatch between the actual braking and steering and the predictions of the driver model. AEB was then activated if there was no reaction by the driver to the mismatch-behavior warning, or if the reaction was too delayed. Assessments of different driver response models regarding reaction time for the same FCW system (i.e., car-to-TW rear-end crash during overtaking) were further studied by Kovaceva et al. (Kovaceva et al., 2022), who found that behavior-based FCW could mitigate safety with different driver response models. Since the traditional required-deceleration-based AEB systems only include vehicle’s deceleration constraints, when the trigger is activated before the CZB is reached, false-positive activations occur. Further, drivers' CZBs have been used in driver models for car-to-car AEB (Brännström et al., 2010; Sander, 2018), pedestrian AEB (Edwards et al., 2015) and cyclist AEB (Duan et al., 2017) and they showed the potential safety benefits with CZB-based AEB Driver behaviors could also be included in conflict and crash avoidance system designs for higher-level automation, like ADS algorithm designs

(Rehder et al., 2017; C. Wei et al., 2019). Human-like or human-oriented behavior was included in vehicle motion control in one study in order to ensure smooth, comfortable trajectories with automated driving algorithms (C. Wei et al., 2019). This finding is highly relevant, as a study by Peng et al. (2022), among others, showed that human-like driving was preferred by occupants of ADSs.

This work includes CZBs in crash avoidance (AEB) system algorithms. The CZB-based AEB only triggers when a crash is unavoidable within the road-user's CZBs. In this context, road users' CZBs (longitudinal and lateral) are represented by maximum comfortable steering and braking maneuvers; their values were based on the literature (Bärgman, Smith, et al., 2015; Brännström et al., 2014; C-NCAP, 2018; Costa et al., 2019; Kiefer et al., 2003). The CZB-based AEB triggers when a crash is not avoidable with the car driver's and TW rider's comfortable steering and/or braking maneuvers. We compared five different CZB-based AEBs, made up of different combinations of steering and braking maneuvers. A CZB-based AEB that includes only the CZB model related to driver braking, for example, will trigger when the crash is unavoidable if the driver only brakes comfortably (as shown in Figure 2). A CZB-based AEB that includes the CZB models related to both driver and rider braking and steering will trigger at the moment when, with both driver and rider comfortably braking and/or steering, the crash is unavoidable. Braking and steering maneuvers (and their respective CZBs in the AEB algorithm) are simulated separately.

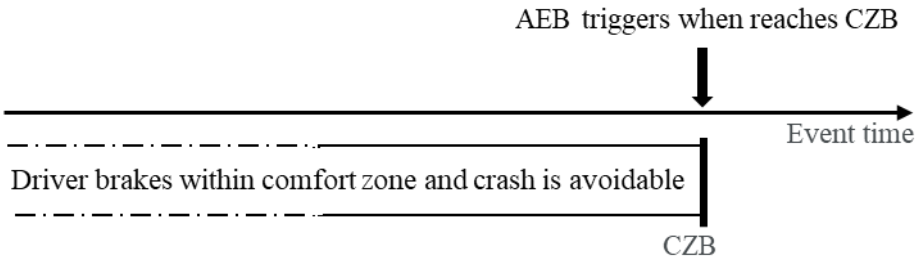

Figure 2: Illustration of CZB-based AEB only including driver brake.

CZB-based AEBs were compared with a traditional required-deceleration based AEB (without driver behaviors) to compare their safety benefits regarding crash avoidance and injury risk mitigation. The injury risks were calculated using an injury risk function for motorcyclists (Ding et al., 2019).

2.2.2 Driver behavior models as part of crash-causation models for scenario generation

Driver models are commonly used in simulating traffic interactions (for example, in traffic simulation and counterfactual simulations). There are reasons why crashes happen, and many studies have been conducted to investigate risk factors for driving. Since driver error contributes to almost all crashes, drivers' risk factors such as inattention, which occurs when driver's attention is not focused on driving, merit special attention. Driver inattention is a factor in over half of police-reported crashes (Stutts et al., 2001). Inattention plays an especially important role in rear-end collisions: Knipling et al. (1993) suggested that driver inattention was implicated in 90% of rear-end collisions occurring on straight roadways. Therefore, driver glance behavior, as a crucial indicator of attention, can be used in crash-causation models in rear-end scenarios on highways. An example of the use of glance-behavior-based crash-causation models is the work by BMW; see the L3Pilot report (Bjorvatn et al., 2021) and the work by Fries & Fahrenkrog (2021). Other examples include glances as

crash causation for assessing behaviors (J. Y. Lee et al., 2018; Victor et al., 2015) and glances in combination with braking behavior (Bärgman et al., 2022) and in relation to levels of automation (Bärgman & Victor, 2019). These driver glance-related studies emphasize the importance of driver models in scenario generation. Scenario generation can also use more simplistic models or different levels of braking response, such as delays in the reaction time to collision warnings (Kusano & Gabler, 2012). A comparison of a glance-based crash-causation model, a traditional response model (based on Kusano and Gabler's 2012 paper), and an improved traditional response model was performed by Bärgman et al. (2022). Their results showed that the choice of model significantly impacts the outcome; further, the glance-based crash-causation model performed the best, as it generated the least derived error compared with the original data.

This work includes driver off-road glance behavior as a core crash-causation mechanism. That is, as off-road glances are the major cause of highway rear-end crashes and drivers can react with different braking levels to a frontal braking vehicle, the same glance-and-deceleration-based crash-causation model used by Bärgman et al. (2022) was used to generate rear-end crashes in this study. There is no evidence of a correlation between glance and deceleration, so they were assumed to be independent. Further, in this study the braking behavior by the driver of the following vehicle was removed and replaced by a simple looming model (Bärgman, Lisovskaja, et al., 2015) and the glance-and-deceleration model described above. In the simulations, the driver was assumed to be attentive (after looking back at the road) and to react by braking according to the looming model, with a braking level based on the fitted maximum deceleration distribution. As a result, each original crash generate 1005 cases (1005 cases: 67 (glance) x 15 (deceleration) combinations). With 44 original cases, 44,220 baseline cases were generated—a challenge to sample, if the simulations take longer than real time.

2.3 Sampling methods in scenario generation

Sampling methods play an important role in generating concrete scenarios based on logical scenarios. Safety assessments of conflict and crash avoidance systems require not only the range of the parameters of logical scenarios but also their distributions, in order to conduct safety benefit assessments that consider exposure.

The standard method for sampling parameter distributions is the Monte Carlo simulation. To solve the time and resource issue in scenario generation, different accelerated approaches have been used—including extreme value theory, and importance sampling theory. Åsljung et al. (2017) used extreme value theory to predict the safety performance of a system based on critical metrics (e.g., brake threat number and TTC), and Wang et al. (2021) applied importance sampling with a reachability analysis to pedestrian crossing scenarios generating realistic scenarios which were also physically feasible. Importance sampling is unbiased and uses available prior knowledge about what combinations of parameters will generate the scenarios that may influence the outcome the most. Consequently, importance sampling typically saves simulation resources by avoiding non-critical scenarios (Swiler & West, 2010). However, it is challenging to implement traditional importance sampling efficiently in practice, as prior knowledge about what impacts crash severity does not always exist. When we know little or guess wrong, the importance sampling may perform poorly.

The active sampling method proposed in this work does not require prior information to the same extent, using machine learning instead to update the sampling scheme based on the new simulation results. The sampling process is shown in Figure 3. The initial simulations represent the most severe crashes for each case (by choosing the longest off-road glance and the lowest deceleration). An initial sampling scheme is then built on the initial simulation

results (whether there was a crash or not and impact speed). These results are assessment targets commonly used to quantify the safety benefit of the assessed avoidance system. After the targets of the first initial simulations are known, the targets of all unchosen simulations are predicted by a classification regression model and a forest regression model, based on the known simulations. The sampling probability is calculated to estimate the target means. A new batch of samples is chosen by the updated sampling probability, and the new simulation results then contribute to the next round of predictions. This iterative sampling strategy, inspired by machine-learning, was applied in the scenario generation in this work.

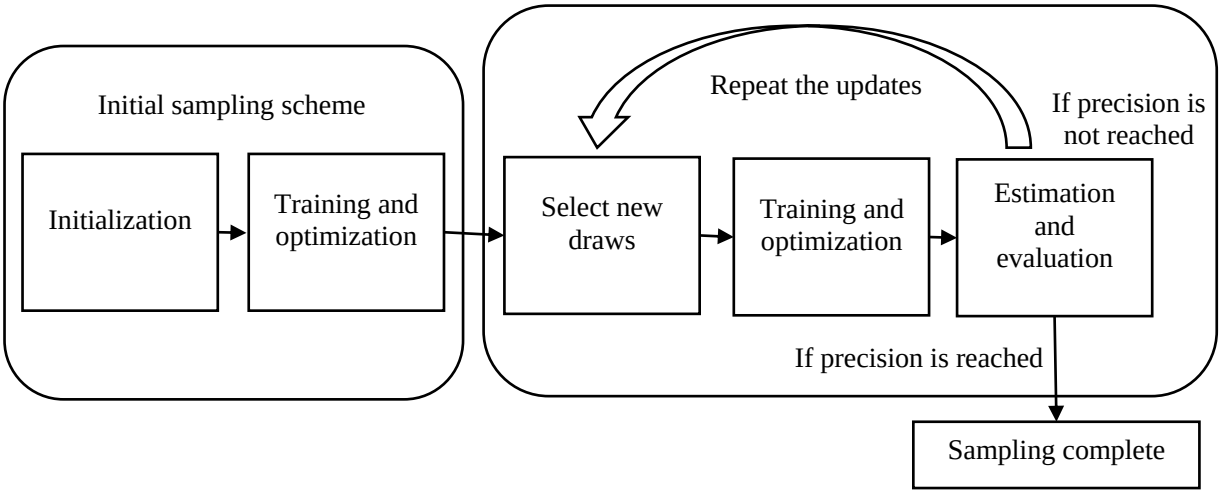

Figure 3: Sampling process of the proposed optimal sub-sampling method

Targets for sampling are chosen explicitly within the appropriate context of safety assessment. Different indicators can be used as safety and benefit metrics depending on the research focus. For example, metrics like TTC, brake threat number, and steering threat number can be used to evaluate the situation's criticality (Brännström et al., 2008). Because this work focuses on safety benefit assessment and crash situations (rather than near-crash and comfort scenarios), the evaluation metrics in this work are impact speed reduction and crash avoidance rate.

3 Summary of papers

Paper I

Yang, X.; Lubbe, N.; Bärgman, J., 2022. Automated Emergency Braking algorithms based on comfort zone boundaries outperform traditional algorithm: Virtual benefit assessment for car-to-two-wheeler crashes in China. Under review.

Author's contribution: wrote the first draft of the paper. Was responsible for the simulation setup, development and implementation of the models and the evaluated AEBs. Performed the simulations, did most of the analysis, and contributed to the synthesis of results and conclusions.

Paper II

Imberg, H., Yang, X., Flannagan, C., & Bärgman, J. (2022). Active sampling: A machine-learning-assisted framework for finite population inference with optimal subsamples. arXiv, preprint: [2212.10024] (arxiv.org). Under review.

Author's contribution: contributed to the setup of the crash causation and counterfactual AEB simulations used as the application (motivating example) in the paper. Applied the active sampling (from the first author), and structured and analyzed results from the simulations. Together with other authors, wrote part of the paper, and contributed to the interpretation of results and to the conclusions.

Paper I: Automated Emergency Braking algorithms based on comfort zone boundaries outperform traditional algorithm: Virtual benefit assessment for car-to-two-wheeler crashes in China

Introduction

With an increasing number of powered-two-wheelers (PTWs) in China, crashes involving PTWs constitute a large proportion of Chinese traffic crashes. Automated Emergency Braking (AEB) systems have been shown to be effective in preventing or mitigating car-to-car, car-to-pedestrian, and car-to-cyclist crashes, but few have studied on-car AEB for conflicts between cars and PTWs. As previous studies have shown the benefits of including road users' comfort zone boundaries (CZBs) in AEB algorithms for other types of AEB, their inclusion in (two-wheeler) TW AEB should also be investigated.

Methods

A CZB model with different thresholds was used to assess the performance impact of including CZBs in AEB algorithms for car-to-PTW conflicts. The CZB-based AEBs trigger when road users cannot avoid a crash by comfortable braking or/and steering maneuver(s). Five different CZB-based AEBs were compared with a traditional required-deceleration-based AEB using counterfactual simulation, applied to SHUFO pre-crash kinematics data. The different AEB systems were also compared with each other, to assess their safety performance regarding crash avoidance rate and injury mitigation. Residual crash characteristics were studied with respect to impact speed and location.

Results

The CZB-based AEB that considered driver braking and steering, to avoid nuisance interventions, performed substantially better than the traditional AEB. That is the CZB-based AEB avoided 72% of the original crashes, while the traditional AEB avoided 48%. When only interventions that occurred earlier than the traditional AEB were considered, all CZB-based algorithms (naturally) performed better than the traditional AEB. In addition, the residual crashes for the different AEBs shared similarities in impact speed distribution and impact location distribution.

Conclusions

Road user participants' CZB can be included in AEB system design to improve system performance. Our study further shows that there are similarities in residual crashes after different AEB implementations, which may simplify the future design of in-crash protection systems—at least for the Chinese market.

Paper II: Active sampling: A machine-learning-assisted framework for finite population inference with optimal subsamples

Introduction

Sub-sampling has been a research topic for a long time. However, as virtual simulations emerge as a crucial tool for the development and assessment of safety systems, the need to complete such simulations in a timely and cost-effective way has emphasized its importance. Traditional sub-sampling methods usually require prior knowledge of the underlying data, which is often not available or of poor quality. There is therefore a need to develop new sampling methods that do not require prior knowledge but performs at least equally well.

Methods

A machine-learning-assisted framework for an optimal sampling method is proposed and applied in this work. Active sampling iteratively updates the sampling scheme based on the previously chosen sub-samples until the chosen samples have reached a desired estimated mean precision. Optimization of the sampling to estimate the benefits of an Automated Emergency Braking (AEB) system with respect to mean impact speed reduction and crash avoidance rate is used for as a motivating example.

Results

The proposed active sampling method with model uncertainty performed much better than the naïve approach (without uncertainty); more importantly, it also performed better than traditional importance sampling methods—especially when optimized on the characterized parameters (mean impact speed reduction and crash avoidance rate). The results also illustrated and assessed the performance of three different variance estimation methods for stopping the simulation (sampling) based on precision. Among them, the classical survey method was the most efficient, performing as well as bootstrapping for different batch sizes.

Conclusions

The proposed machine-learning-assisted framework was applied to a motivating example for a crash avoidance system assessment, showing the benefits of the proposed active sampling method over traditional sampling methods. The proposed active sampling method has the potential to be used in scenario generation and virtual simulations across conflict and crash avoidance safety assessments as well as across scenarios, facilitating faster assessment and consequently better systems. In addition, three variance estimation methods were assessed for active sampling.

4 Discussion

This work aims to improve the performance of conflict and crash avoidance systems that are part of both ADAS and higher levels of automation. Crash avoidance systems like TW AEB (Paper I) have the potential to improve traffic safety when road user behaviors are included in the systems' designs. Section 4.1 discusses Paper I, which addresses the first objective of this thesis (investigating CZB-based driver models in crash avoidance systems). The discussion on virtual safety assessments and their inclusion of driver models is in Section 4.2. Section 4.3 discusses the subsampling methods proposed, and demonstrated, in Paper II. The optimal subsampling method for virtual safety assessment was applied to the generation of rear-end scenarios using a glance-and-deceleration-based crash-causation model. A novel stopping criteria for simulations and experiments is also described in future work in Section 4.4.

4.1 The use of driver models in conflict and crash avoidance systems

Most of the CZB-based TW AEB algorithms proposed in this work were better at avoiding and mitigating crashes than the traditional (required-deceleration-based) AEB algorithm. Specifically, the TW AEBs could trigger earlier than the traditional AEB when road users' CZBs (for braking or steering to avoid a crash) were reached earlier than the vehicles' physical constraints (at the point of no return). On the other hand, the traditional AEB could trigger earlier in the opposite situation, when the CZBs were reached after the point of no return. In those situations, road users still had the potential to avoid the crash themselves. That is, the traditional AEB risked triggering false positives, which could be a nuisance to drivers. For example, the trigger time difference between the CZB-based AEB which included drivers' and riders' braking and steering maneuvers and the traditional AEB for the cases where the traditional AEB triggers before the CZB-based AEB are shown in Figure 4. It shows a 0.4 s earlier trigger time (on average) for the required-deceleration-based AEB. When the traditional AEB triggers earlier than the CZB-based AEB, the road users still have the potential to avoid the crash themselves "comfortably" (per the definition of comfort used in Paper I). A similar difference in trigger time (traditional AEB triggering before the CZ-based) may also occur in straight front-to-front (also called head-on) scenarios, where there is still a chance to avoid the crash by steering (but not by braking). Another situation where this earlier trigger by traditional AEB may occur is when there is a small overlap between the two road users in a rear-end situation, such as when a PTW is driving on the edge of the road and a car is driving more in the middle of the lane; the driver only needs to make a small, comfortable steering adjustment (which can be performed quite late) to avoid a crash. For example, a small lateral movement of the car may suffice to avoid a crash in an overtaking scenario. The larger the difference in trigger times between the traditional and the comfort-based trigger, the greater the nuisance of the traditional one for the driver. The delay in intervention after the traditional AEB triggers reduces the performance of CZB-based AEBs that include comfort constraints (the more constraints, the lower the performance: see Table 4 in Paper I). However, nuisance interventions are typically not a problem for AEBs; they commonly have a relatively high acceptance rate (N. Mohd Ishanuddin et al., 2021; Nuruzzakiyah Mohd Ishanuddin et al., 2022; Reagan et al., 2018). It is likely that car manufacturers do include rules in the AEB algorithms that avoid interventions in, for example, the TW or car overtaking situations described above. It would be reasonable to keep those rules or change them to a CZB-based solution. Using CZB-based algorithms may make it possible to improve the overall performance by allowing earlier triggers, at even lower decelerations (thus minimizing the risk of rear-end conflicts between the following vehicle and the vehicle behind it). Nuisance considerations need to be investigated further in open research.

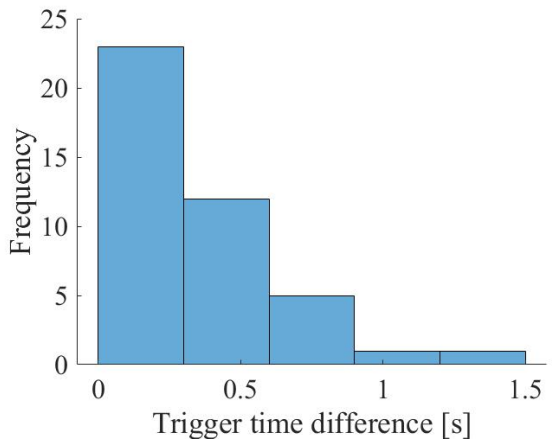

Figure 4: A frequency histogram of the earlier trigger time (i.e., only the positive y-axis values in Figure 4 in Paper I) of required-deceleration-based AEB compared to CZB-based AEB (including driver and rider braking and steering maneuvers).

To be effective, CZB-based AEBs must include CZBs that are reasonably accurate; the boundary constraints need to come from reliable data. In this work the constraints are drawn from different driver behavior studies. One study by Bärgman et al. (2015), providing data from guided experiments on test tracks for 22 participants, defined comfort zones in the context of comfortable driving and hurried driving. They reported a maximum comfortable lateral acceleration of around 5 m/s^2 (in left turns). In another study, participants were instructed to drive normally reached a maximum braking deceleration of 5 m/s^2 (Hugemann & Nickel, 2003). Further, Sander (2018) based his selection of CZBs for the AEB evaluated in his work on experimental and naturalistic driving data (Bärgman, Smith, et al., 2015; Dingus et al., 2006; Moon & Yi, 2008) and suggested that 5 m/s^2 could be a reasonable starting value for maximum deceleration in such AEBs.

It is important to note that the CZBs used in this work were derived using the upper limit across drivers (i.e., it can be considered the CZB for most drivers), even though an individual driver may have a different CZB (i.e., react differently) in a real situation. Sander investigated 3 m/s^2 and 7 m/s^2 as thresholds, applying them to crashes to test the crash avoidance system performance. He found that system performance increased around 10% for 3 m/s^2 and decreased around 10% for 7 m/s^2, compared with a CZB (threshold) of 5 m/s^2. In future studies, the specific CZB threshold values should have further sensitivity analyses performed for both critical and non-critical situations, to assess system safety and false-positive performance across a set of drivers; car-to-VRU scenarios should be included. Collected field data has been applied to the analysis of false positives. For example, Dozza et al. (2020) assessed their “smart collision avoidance system”, which first issued a warning when the driver behaved differently from the driver model prediction; then, if there was no reaction to the warning (or the reaction was too delayed), the AEB was triggered. This type of open (i.e., published research) assessment should also be made for the TW AEB in the future.

The most important aspect of a conflict or crash avoidance system’s performance (in addition to keeping all road users safe) is the driver’s potential, rather than what TW riders (or other road users) feel. The CZB of the vehicle driver is relevant, while the CZB of TW riders (as used in Paper I) should preferably be what the car driver assumes the TW is able to do comfortably (rather than the TW rider’s actual CZBs). That is why the CZB model in the TW AEB assessed here is based on the driver’s mental model of what actions the TW rider could have done comfortably. However, a problem here is that there is a major lack of CZB data. In

the literature review for Paper I, there are no previous studies about drivers' mental models of the CZB of TWs (or any other road users). Such data could be used to design the AEB activations more precisely. We also found no relevant studies about TW riders' CZBs. This dearth may not, however, be that significant in this particular case, since we used the CZB of a car driver as the driver's mental model of the CZB of a TW rider. We argue that this is reasonable, as most drivers project their own experience as drivers onto the actions of the TW rider (although drivers who are also TW riders might not). It is not clear to what extent the driver's CZB model of the other road users actually matters in the driver's consideration of a nuisance intervention (or warning, if it is a warning system). This aspect of CZB models should be investigated in future studies.

The focus of Paper I is crash avoidance and the investigation of the performance benefits of CZB driver models in the design of crash avoidance systems. In addition to their application in crash avoidance systems, driver models (such as CZBs) also have substantial potential to improve conflict avoidance systems, both in ADAS and higher-level automation vehicle systems. Research has found that in the domain of ADAS, crash avoidance systems have a higher usage rate than conflict avoidance systems (Reagan et al., 2018); including driver behavior models in ADAS conflict avoidance systems like lane keeping systems may increase their acceptance and usage. Actually, many ACC systems already consider drivers' CZBs—by allowing the drivers to explicitly set a (time or distance) gap to the lead vehicle which they are comfortable with.. Moon & Yi (2008) designed the ACC system based on the driver behaviors and such ACC system showed similar following performance compared to human manual driving in high-speed driving and low-speed traffic jam situations (Moon & Yi, 2008).

For higher-level systems, researchers have investigated the use of driving algorithms based on natural driving styles, and studied driver acceptance of the algorithms. Bellem et al. (2016, 2018) investigated how drivers accept higher-level automation systems by including different driving styles for drivers to choose from (e.g., a comfortable or a dynamic driving style). Wei et al. (2019) investigated human-driven vehicle behavior and used it in the ADS trajectory algorithm. The same algorithm was further assessed in a driving simulator study compared with a machine-learning-based algorithm and the results showed human-like driving styles to be more comfortable and natural than machine-learning-based driving styles, based on participants' responses to questionnaires (Peng et al., 2022). Based on the literature, it may be argued that including driver behavior (e.g., explicit information about drivers' CZB) in higher-level automation vehicle systems could improve drivers' acceptance, perhaps as a complement to the machine-learning-based driving. However, this also needs to be investigated further.

As conflict and crash avoidance systems continue to develop, they will not only impact vehicles' safety performance in terms of crash avoidance, but also the crash population of the future. Estimating the characteristics of residual crashes after conflict and avoidance systems are available on our roads may help developers of in-crash protection systems optimize their systems—not only for today's crash characteristics, but also for those of the future. Paper I specifically showed that the impact speed and impact location distributions of the residual crashes were similar across AEBs (the proposed CZB-based AEBs and the traditional required-deceleration-based AEB). Compared to the original crashes, the TW AEB systems reduced the impact speeds and increased the proportion of corner impacts. These results are supported by others' work; Jeppsson and Lubbe's simulation results showed that corner impacts increased after AEB implementation (2020). Information about future crash characteristics can impact the way that in-crash protection system are designed. The increase

in corner impacts reported in Paper I indicates that A-pillar protection and side airbag may be needed in a future where TW AEB are ubiquitous.

4.2 The use of driver models in traffic safety assessment

In addition to being included in conflict and crash avoidance system designs, driver models can be included in crash-causation models, which mathematically describe the mechanisms behind crashes. The crash-causation models can then be used as part of a virtual assessment of conflict and crash avoidance systems. Rear-end crashes are one of the most common crash types; in those scenarios, visual attention and braking behavior are crucial factors. Therefore, this work adopted a crash-causation model based on glance and deceleration in order to create rear-end crashes for manually driven cars (without automation). The same model was used by Bärgman et al. (2022), who compared crashes generated by this model and crashes generated with a traditional reaction model by applying scenario generation approaches to a set of reconstructed rear-end crashes. Their results suggested that crash-causation-model-based scenario generation is a promising method for virtual safety assessment of traffic safety—in general, and for crash avoidance systems in particular. The traditional reaction model is based on the work of Kusano and Gabler (2012). In fact, many driving simulator studies that investigate reaction time distributions (typically to quantify delays related to for example cognitive load or some visual manual task) use driver reaction times to the onset of a lead vehicle braking as a main safety metric (Markkula et al., 2016). The results from the Bärgman et al. (2022) study show that, compared to the impact speed distribution of the reaction model-based generated crashes, the distribution of the crashes generated through virtual simulation with glance-and-deceleration-based crash causation are more similar to the original impact speed distribution. Similarly, a driver glance-and-reaction model has been used by other researchers in scenario generation for crashes in which backing out or reverse driving maneuvers are involved, but the outcomes of the generated baseline were not compared with the outcome of the original crashes to validate their method (Funke et al., 2011). Also, BMW has developed a stochastic cognitive driver model (SCM) and demonstrated its application it in a passive cut-in scenario. The results show similarities between the generated data and real-world data (Fries et al., 2022), but an in-depth validation has not yet been published. While the models described above are driver reaction-based crash-causation models, it is also possible to build statistical models based on specific factors as input and the crash as output'. One example is the Bayesian network model created by Song et al. (2022) who investigated dependencies among crash characteristics and crash outcomes based on a big dataset (about 150,000 crash observations). They used a Bayesian network to model the dependencies in order to enable scenario generation. However, statistical methods need a lot of data to get accurate crash outcome predictions. Future studies should compare this approach with the crash-causation-model based approach for scenario generation to determine which is more accurate and precise, or maybe just to acknowledge that they are complementary.

Although not directly relevant for this thesis, in this section it is worth mentioning another use of driver models—as reference driver models for the assessment of higher-level automation. Reference driver models are currently used to represent a specific type of driver, like a competent and careful one. They do not necessarily need to represent all human behaviors during different driving tasks, but instead could be used to assess whether a crash is preventable by a competent and careful driver (for example). In addition to the reference models which are part of Regulation 157 (UNECE, 2021), Mattas et al. (2022) suggested a "fuzzy safety model" (FSM), which they argue can mimic defensive drivers by capturing their comfortable braking behaviors for conflict avoidance (they tend to avoid emergencies in advance). The Waymo NIEON model described earlier is another example of a reference

driver model (Scanlon et al., 2022). Accurate CZB models can be used as components in the development of such a reference model, perhaps enabling better safety assessment of conflict and crash avoidance systems. Therefore, more work is needed to operationalize CZB collection across scenarios—for use in both conflict and crash avoidance system designs, and in the assessment of such systems.

4.3 Statistical methods in virtual simulation assessments

The performance of conflict and crash avoidance systems can be improved not only by using driver models in system design and assessment, but also by including more efficient statistical methods in the assessment. The machine learning-based active sampling method proposed and implemented in Paper II outperformed traditional importance sampling. The active sampling method required fewer simulations than the traditional importance sampling method to reach the same estimated error level. Unlike the active sampling method, the importance sampling method has a fixed sampling scheme, so newly collected samples do not add more information. Further, if the fixed sampling scheme chosen in traditional important sampling is far from the best (i.e., if it always picks samples with little information), the sampling may perform even more poorly. In Paper II, two different importance sampling methods were compared with the proposed active sampling one. The two importance sampling methods performed differently, but both were worse than active sampling (as shown in Figure 3 in Paper II).

Importance sampling relies on prior information, which determines the parameter density for sampling. In our application, the prior information used in both importance sampling methods comprised a glance-deceleration distribution and maximum impact speed for each case (for severe importance sampling in Paper II). Active sampling, on the other hand, does not need prior information to build sampling schemes. Instead, active sampling needs a set of samples to initialize the sampling scheme while importance sampling does not. The initial samples in the scenario generation application in Paper II were made up of the most severe scenario for each case, but for different applications it may be more difficult to pick initial samples. Active sampling updates the sampling scheme with the known samples; as the prediction model relies on known samples, the more simulations run, the more accurate the prediction model and the more efficient the sampling scheme. As a consequence, active sampling may perform less well than importance sampling for a small sample size but is likely to perform better as sample sizes increase. If the actual total sample size required is small and prior information is known, importance sampling is likely a good choice; however, if the sample size required is large and/or prior information is missing, active sampling is likely a better choice. It should be acknowledged that there are several other ways to sample efficiently. For example, De Gelder & Paardekooper (2017) conducted importance sampling based on kernel density estimation to generate scenarios using available real-world driving data. The method proposed in their application showed the potential of importance sampling to identify critical scenarios and relative error estimation (near-crash and crash occurrences), but the method relied on a large amount of available data, which the active sampling approach typically does not.

The performance of different sampling methods can be assessed and evaluated by measuring the root mean squared error. Figure 3 in Paper II shows the evaluated error compared with the ground truth (all information about the sampling pool) to demonstrate the performance of different sampling methods. In practice, however, the ground truth is typically unknown; if the results were known, we would not need to do any simulations. However, methods for estimating the error without ground truth information are needed in order to design stopping criteria in the sampling process (such as the three methods of estimation of variance used in

Paper II). Knowing when to stop—when enough scenarios have been generated—is not always included in scenario generation literature. For example, De Gelder and Paardekooper (2017) planned it as part of future work. In this work, the bootstrap method (Efron, 2007), the Martingale method (B. M. Brown, 1971), and the classical survey method (Sen-Yates-Grundy estimator) (Sen, 1953; Yates & Grundy, 1953) were applied. The Martingale method and the classical survey method are parametric variance estimation methods (the former uses the squared variation of the estimates and the latter uses a pooled estimator of the conditional variances), while the bootstrap method is non-parametric. The bootstrap method is more time-consuming and computationally heavier than the other two methods, as it repeatedly resamples datasets. The 95% coverage results in Paper II show that the Martingale method performed worse for a large sample size than the other two. In contrast, the bootstrap and classical survey methods performed well for both small and large batch sizes (with the number of samples updated per iteration), except that the classical survey method needs a batch size of at least two (based on its theory). Due to the longer computation time of the bootstrap method, classical survey methods are typically recommended for deciding when to stop when you estimate a relatively large batch size, while the Martingale method is better for small batch sizes. For our application in Paper II, with 44 original cases, the batch size (over ten) is relatively large. However, while these variance estimation methods can be used to estimate whether the collected data are enough, they are not suitable for justifying whether ongoing experiments or simulations are worthy of further pursuit. In parallel with the work described in this thesis, a Bayesian prediction-stopping method has been investigated, to resolve this issue. This work is briefly described below.

4.4 Limitations and future work

Both counterfactual simulation and scenario generation methods used in this work were heavily dependent on the available data. Without available crash data, neither methods can be used, and the accuracy and representativeness of the simulation results are influenced by the amount of data as well. To assess the CZB-based crash avoidance systems in Paper I, 93 car-to-TW crashes from the SHUFO database were used. The sensors used in the virtual simulations are idealized, with no uncertainties and errors in the detection and tracking of other road users. However, in the real world, sensors are not ideal; the performance of the crash avoidance system in the simulations are typically substantially better than in the real world as a result. Sensor limitations should be added in future simulations to enable more realistic system performance estimation. In addition, the driver and rider models were simplified with a single-track bicycle, which may have influenced the simulation results.

The rear-end crash scenario in Paper II is a relatively simple scenario and it was sufficient to demonstrate scenario generation—and the application of the active sampling method in scenario generation. However, there is much work needed to generalize crash-causation models to other scenarios. The glance-deceleration model could be used as a crash-causation model for highway rear-end crashes, but it is not suitable for more complicated scenarios, such as car-to-VRU interactions. Unlike rear-end crashes, with a main crash mechanism of visual attention toward the forward roadway, car-to-VRU crashes require more work before it is possible to apply crash-causation model-based scenario generation to them. The proposed active sampling method could also be implemented in car-to-VRU scenario generation, but the crash-causation-mechanism model would need to be developed first. Also note that depending on the scenario, there may be a dominant crash-causation mechanism (e.g., inattention for rear-end crashes), or several main mechanisms (likely true for car-to-VRU crashes). If the latter, each mechanism needs to be modeled, and the proportion of crashes that

each “causes” in the real world needs to be considered when the scenario generation framework is created for a particular concrete scenario.

Further, the proposed active sampling method presented in Paper II optimizes the sampling on the mean. In the future, different optimization targets can be used. For example, to identify (or generate) extreme cases, the active sampling method could be updated to optimize for extreme cases. Further, to identify a target parameterized distribution, the active sampling method could be changed to optimize for such a distribution (with some parameter defined, such as an impact-speed or injury-risk-curve distribution for log normal distribution). To do the latter, however, one has to understand which distribution is likely to be a good fit. More complex distribution mixes can be included, but more work is needed to integrate them into the current sampling method.

The scope of this thesis is limited to crash avoidance safety assessment. In the future, conflict avoidance and crash avoidance should be investigated together. Although crash avoidance is important for higher levels of automation, the conflict avoidance components of higher levels of automation are really crucial for safety (Scanlon et al., 2022). Future work should study both actual safety system evaluation (as in Paper I) and methods for sampling and scenario generation for conflict avoidance systems as well. As noted, scenarios were generated with a simple crash-causation model for rear-end crashes. In the future, scenario generation should also be considered for more complicated scenarios, such as car-to-VRU scenarios.

Three methods (bootstrap, Martingale, and classical survey) were utilized in Paper II to evaluate whether the current collected sample (simulations) was enough to stop simulation regarding a specific precision. These methods do not (and cannot) estimate future data collection, being based on already-performed simulations. “Looking into the future” is often not necessary, as the aim is either to continue to run simulations until a specific precision is reached or to end the simulations when time or resources are depleted. However, there are situations where estimating if it is feasible to actually reach the sought precision would be highly beneficial: when seeking to minimize resources for simulations or (even more) when conducting (very expensive) experiments with human participants. An example of the latter would be developing models of driver behavior or assessing the performance of a specific safety system as part of an industry project. A method providing a stop point would be relevant when an organization wants to continue to run a specific simulation or test-track experiment until the desired precision is reached, but may not have sufficient resources to continue until the stopping criterion is reached. In particular, it is a concern when applying Bayesian statistics, if a precision target is set, that Bayesian stopping criteria may result in a more or less infinite number of simulations or experiments—known as the “black hole” issue (Marolf, 2017). It would be highly beneficial to know if the resources are likely to run out before needed samples (to reach the precision) are likely to be collected, and stop the experiment if it is not likely to provide useful results.

Due to concerns about the black hole issue described above, in parallel to the work presented in this thesis I have been pursuing the development and application of a method to predictively end simulations or experiments based on an extrapolation of future samples. Progress has been made, but challenges remain: when the sample size is relatively small, the prediction can be correspondingly less reliable. So either a reliable prediction starting sample size needs to be defined, or a correction model needs to be added. Future work includes applying the method to an example study. The method is the equivalent of running a (frequentist) power analysis, albeit based on collected data. This type of stopping criteria can

help optimize resource use in the development of models of driver behavior (for use in virtual simulation), and possibly as a part in virtual simulations directly.

5 Conclusions

This work contributes to the field of research seeking to improve traffic safety using computational driver models, both in conflict and crash avoidance systems (integral parts of ADAS and ADS) and in the methods used to assess the systems' impact on safety. Specifically, this work investigates the usage of i) driver models based on comfort-zone boundaries (CZB) in crash avoidance system designs; ii) optimal subsampling together with a driver behavior-based crash causation model in scenario generation. The results presented in this thesis suggest that driver behavior models should be included in crash avoidance systems to improve their safety performance. In Paper I, CZBs for driver braking and steering maneuvers were used in AEB system designs to improve the systems' crash avoidance and injury mitigation and lower the potential for false-positive interventions. The results show that CZB-based AEBs performed almost 50% better than the traditional AEB, and likely would result in fewer nuisance interventions. Actually, it may also be worth investigating other applications using driver models with CZBs in both ADAS and ADS development. Further, similarities in residual car-to-PTW crashes across algorithms may simplify future in-crash protection system designs. The practical impact of these results will likely be safer roads through both a) improved crash and conflict avoidance systems and b) in-crash protection systems that target future (remaining) crashes effectively. The indicated 50% improvement over traditional AEB algorithms means that this research may truly contribute to saving lives.

Driver models can be used not only in system designs but also as an integral part of virtual safety assessments. Consequently, a driver behavior model was also included as a crash causation component in the virtual simulation in Paper II. The focus of Paper II was an assessment of, not a specific crash avoidance system, but an optimal subsampling method combined with a crash causation model. While the method can make safety assessments more efficient generally, the particular application here is to scenario-based virtual simulations that include computational driver models. When the number of parameters increases, the number of scenarios that need to be simulated increases combinatorially; the traditional sampling method can be inefficient when prior information is missing or inadequate. The machine-learning-assisted active sampling method proposed in Paper II is intended to improve assessment efficiency (even with less prior information) and overcome some of the other drawbacks of traditional important sampling methods. Specifically, the methods proposed in this thesis need fewer simulations than traditional methods to reach the same target precision. In our specific application, active sampling required almost 50% fewer simulations than importance sampling for large sample sizes, reducing the time and resources needed to a corresponding degree.

This improved efficiency is also likely to be beneficial in virtual safety assessments of not only conflict and crash avoidance systems, but also in-crash protection systems. For example, human body model (HBM) simulations to assess in-crash safety systems are often much more time-consuming than pre-crash simulations; the proposed sampling method is likely to reduce the overall simulation time (by reducing the number of simulations required) substantially. Although the practical implications of the reduced simulation time (potentially both for pre-crash and in-crash simulations) are hard to quantify, they may well result in faster development time and correspondingly faster release of better products to save lives on our roads.

Future work aims to apply the proposed sampling method to other scenarios (like car-to-VRU scenarios) for virtual safety assessments using driver behavior models of other conflict and crash avoidance systems. In addition, I will work on developing a resource-limitation-focused

Bayesian prediction-based stopping criterion for experiments and simulations. The criterion will support the decision whether to continue or end experiments and simulations early by identifying when the available resources are sufficient to yield significant (or the Bayesian equivalent) results.

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