



ELSEVIER

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Crash probability estimation via quantifying driver hazard perception

Yang Li^a, Yang Zheng^{a,b}, Jianqiang Wang^{a,*}, Kenji Kodaka^c, Keqiang Li^a

^a State Key Laboratory of Automotive Safety and Energy, Tsinghua University, Beijing 100084, China

^b Department of Engineering Science, University of Oxford, United Kingdom

^c Honda R & D Co. Ltd. Automobile R & D Centre, Tochigi 321-3393, Japan

ARTICLE INFO

Keywords:

Crash probability
Driver hazard perception
Field operational test
Rear-end model
Numerical simulation

ABSTRACT

Crash probability estimation is an important method to predict the potential reduction of crash probability contributed by forward collision avoidance technologies (FCATs). In this study, we propose a practical approach to estimate crash probability, which combines a field operational test and numerical simulations of a typical rear-end crash model. To consider driver hazard perception characteristics, we define a novel hazard perception measure, called as driver risk response time, by considering both time-to-collision (TTC) and driver braking response to impending collision risk in a near-crash scenario. Also, we establish a driving database under mixed Chinese traffic conditions based on a CMBS (Collision Mitigation Braking Systems)-equipped vehicle. Applying the crash probability estimation in this database, we estimate the potential decrease in crash probability owing to use of CMBS. A comparison of the results with CMBS on and off shows a 13.7% reduction of crash probability in a typical rear-end near-crash scenario with a one-second delay of driver's braking response. These results indicate that CMBS is positive in collision prevention, especially in the case of inattentive drivers or old drivers. The proposed crash probability estimation offers a practical way for evaluating the safety benefits in the design and testing of FCATs.

1. Introduction

Road accidents currently pose a serious threat to our daily life. Among these, rear-end crashes are the most common accident type around the world (National Highway Traffic Safety Administration, 2014; Traffic Administration Bureau of the Ministry of Public Security of PRC, 2012). Recently, many forward collision avoidance technologies (FCATs) have been developed and employed to avoid or mitigate rear-end collisions by providing warning or automatic braking assistance for drivers (Nodine et al., 2011; Zellner, 2012; Wang et al., 2015a,b; Ruscio et al., 2015).

However, the effectiveness of FCATs in terms of crash avoidance remains unknown for different traffic environments. This issue is currently attracting considerable attentions from both academia and industry (Distner et al., 2009; Kusano and Gabler, 2012; Fildes et al., 2015). Traditionally, the crash avoidance effects of FCATs are evaluated by comparing the crash probability with FCATs on and off. Previous approaches can be roughly categorized into two groups: 1) crash data simulation, which relies on in-depth crash databases (Georgi et al., 2009; Zellner, 2012; Fildes et al., 2015); 2) Field Operational Test (FOT), which aims to evaluate functions under normal operating conditions (McLaughlin et al., 2008; Nodine et al., 2011; Benmimoun et al.,

2013). Naturalistic driving test is a special type of FOTs, which has been considered one of the most valuable methodologies for traffic safety analyses (Klauer et al., 2006; Wisch et al., 2013,b; Wang et al., 2015a,b). Most of these methods consider only the objective data (i.e., crash data or naturalistic driving data), which relatively ignore the role of drivers in the crash avoidance estimation (McLaughlin et al., 2008; Fildes et al., 2015).

On the other hand, driver is one key link between FCATs and the vehicle, which plays an important role in the collision avoidance performance of FCATs. Driver is supposed to make appropriate responses if FCATs initiates a warning or braking assistance. In general, the key factor that influences drivers' responses is driver's hazard perception. Driver hazard perception is a kind of driving ability that enables driver to detect an impending collision risk and make braking or evasive maneuvers to avoid collisions (Borowsky et al., 2012; Crundall et al., 2012; Meir et al., 2014; Markkula et al., 2016). If the driver's perceived collision risk is consistent with activations (i.e., warning or braking) of FCATs, the driver would accept FCATs and take avoidance maneuvers to reduce the collision risk. Conversely, too early warnings or brakes for drivers would decrease driver acceptance, thus weakening the potential crash avoidance effect of FCATs. Therefore, driver hazard perception is essential to crash avoidance effect of FCATs. However, to the best of the

* Corresponding author.

E-mail address: wjqlws@tsinghua.edu.cn (J. Wang).

<http://dx.doi.org/10.1016/j.aap.2017.05.009>

Received 27 November 2016; Received in revised form 10 May 2017; Accepted 12 May 2017
0001-4575/ © 2017 Elsevier Ltd. All rights reserved.

author's knowledge, driver hazard perception is rarely considered in the evaluation on the crash avoidance effect of FCATs in early stages of testing (Zellner, 2012).

This paper proposes a practical crash probability estimation model that takes driver hazard perception characteristics into account. The proposed method is validated by a two-month field operational test based on a Collision Mitigation Braking System (CMBS) equipped vehicle. In the following, we give a literature review on recent researches of both crash reduction estimation and driver hazard perception, and also present an overview of the key results of this paper.

1.1. Crash reduction estimation

Over the past several decades, a considerable number of studies on crash reduction estimation of FCATs have been conducted. Of these studies, crash data simulation and field operational test are the two most widely used approaches.

Crash data simulation relies on in-depth crash investigation databases, such as the National Automotive Sampling System/Crashworthiness Data System (NASS/CDS) (NHTSA, 2014), German In-Depth Accident Study (GIDAS) (Otte et al., 2012). Crashes are reconstructed and re-run with a FCAT functional algorithm in the MATLAB/Simulink environment, to determine how many crashes could have been avoided if an FCAT had been available. For example, NHTSA initiated an Advanced Crash Avoidance Technologies (ACAT) program to develop a safety impact approach (SIM) to estimate the crash reduction contributed by advanced crash avoidance technologies. Honda and Dynamic Research Inc. (DRI), evaluated an advanced collision mitigation braking system (A-CMBS) by using the NASS/CDS database (Zellner, 2012). These studies have offered certain insights to evaluate the effectiveness of FCATs in terms of accident prevention or mitigation. However, crash data simulation can only be conducted based on in-depth accident databases, which are expensive to collect and maintain.

Another important method is the Field Operational Test (FOT). FOT is a large-scale testing project aiming at a comprehensive assessment of the efficiency, quality, robustness and acceptance of intelligent transportation technologies, such as advanced driver assistance systems (Nodine et al., 2011; Benmimoun et al., 2013; Källhammer et al., 2016). For instance, Intelligent Vehicle-based Safety System Field Operational Test (IVBSS FOT) evaluated the safety effects of an integrated crash warning system (Nodine et al., 2011). Also, the effects of eight different Advanced Driver Assistance Systems (ADAS) were investigated within the first large scale field operational test in Europe, namely euroFOT (Benmimoun et al., 2013). Naturalistic driving test refers to studies about unobtrusive observation of driving behavior taking place in its naturalistic setting (Klauer et al., 2006; Dingus et al., 2006). Drivers are expected to be unaware of the discreet data collection and preferably use their own vehicles in the naturalistic driving tests. NDS has been considered one of the most valuable methodologies for traffic safety analyses (Neale et al., 2005; Wisch et al., 2013,b; Wang et al., 2015a,b). However, as there usually occurred very few number of crash incidents in naturalistic driving test, the direct evaluation of FCATs based on real-world crashes is unavailable (Klauer et al., 2006). Instead, the exposure to near-crash can serve as an alternative measure to estimate the potential safety benefits in reducing the number of target crashes (Chin and Quek, 1997; Guo, 2010; Nodine et al., 2011). Wu et al. (2014) explored associations between near-crash (traffic safety-related events) and crash risk at driver level based on naturalistic driving data. For near-crash studies, it is essential to properly define near-crash in order to better identify near-crashes from a naturalistic driving database. The notion of near-crash is similar to a crash in terms of collision risk but without real collision. Currently, there are no widely accepted agreements concerning the definition, identification, and validation of near-crash in traffic studies (Klauer et al., 2006; Guo, 2010; Wu et al., 2014; Wang et al., 2015a,b). In general, a set of rules defined by kinematic

parameters (i.e., longitudinal/lateral acceleration and braking duration) have been applied to identify near-crash from a naturalistic driving database (Nodine et al., 2011; Dozza, 2013). In our study, we aim to propose a practical crash probability estimation method, and then to evaluate the safety performance of Collision Mitigation and Brake Systems (CMBS). Therefore, field operational test (FOT) is employed for our data collection.

1.2. Driver hazard perception

Driver hazard perception is regarded as an important driving ability that enables drivers to detect impending collision risks in complicated traffic environments (Borowsky et al., 2012; Crundall et al., 2012; Meir et al., 2014). There are two predominant hazard perception measures: 1) driver response time to the perceived risk (Sagberg and Bjørnskau, 2006) and 2) the evaluation on the degree of perceived hazard (Borowsky et al., 2012). Sagberg and Bjørnskau (2006) conducted a video-based hazard perception test to measure driver reaction time toward 31 traffic scenes. Borowsky et al. (2012) required drivers to identify hazardous situations while watching hazard perception movies. Crundall et al. (2012) investigated the driver hazard perception by employing video clips taken from the driver's perspective. Each video clips include one or more hazardous cases, such as pedestrian steps into the road from the behind of parked cars. Driver response time is easily measured, but usually tested in limited conditions. The evaluation on the degree of perceive hazard is easily affected by psychological status of the participants and the environment conditions. Moreover, it is not easy to incorporate these hazard perception measures into vehicle dynamic models for crash probability estimation of FCATs. To this end, this study proposes an operational measure of hazard perception to evaluate the crash probability reduction of FCATs, which is based on Time to Collision (TTC) and driver's braking response toward collision risk in a near-crash scenario. This hazard perception is involved in rear-end crash model and associated with crash probability. Thus, it can be easily applied to evaluating the collision avoidance effect of FCATs.

1.3. Preview of key results

In this research, we establish a novel approach for crash probability estimation, as shown in Fig. 1. We first define a novel hazard perception measure which can be easily used in a rear-end crash model. Then, by numerical simulations of the rear-end model, the crash probability is associated with the driver hazard perception measure. To validate this approach, we conduct a real-world field operational test based on one CMBS-equipped vehicle. The field test recorded the normal driving behavior of each driver without any interventions. Based on the recorded data, we established a two-month¹ normal driving database. Then, a crash probability reduction of CMBS is calculated by combining numerical simulations and the normal driving database. Results shows that this crash probability reduction effect contributed by CMBS can achieve 13.7% with a one-second delay of driver's braking response.

The remainder of this paper is organized as follows: Section 2 introduces our driving database and data preparation works. In Section 3, we propose the crash probability estimation approach based on numerical simulations of a rear-end model. We validate the approach by calculating the crash probability reduction effect of CMBS in Section 4. We discuss an outline for future works in Section 5, followed by concluding remarks in Section 6.

2. Driving database and preparation works

In this section, we first introduce the field operational test. Next, a

¹ Two-month test: there were 20 drivers and each driver was in test for three days, so the test lasted for 60 days (two months).

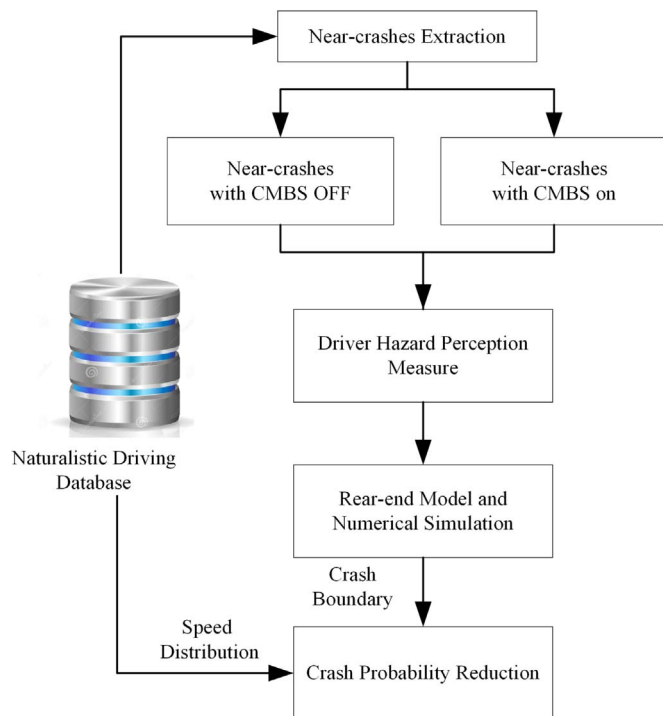


Fig. 1. Flowchart of crash probability estimation approach.

novel hazard perception measure, *i.e.*, driver risk response time, is introduced. Then, we extract near-crash scenarios with CMBS on and off, respectively, to compare driver risk response time.

2.1. Field operational test

We carried out a field operational test using one CMBS-equipped vehicle to collect normal driving data. CMBS is one of FCATs which is designed to avoid and mitigate the rear-end crash (Zellner, 2012).

The CMBS system configuration is shown in Fig. 2. A millimeter-wave radar sensor continuously measures the speed and positions of obstacles on the road ahead. A yaw rate sensor measures pose information of ego vehicle. An electronic control unit (ECU) continuously predicts crash probability with obstacles on forward road. Once the crash probability exceeds a certain safety threshold, a collision warning sound and autonomous braking assistance would be activated to help reduce the collision risk. Simultaneously, motorized safety seat belts would be tightened to reduce occupant injuries. In this study, we focus on safety effect assessment of CMBS contributed by warning function of CMBS.

2.1.1. Data collection system

It is important to obtain high-quality driving data for a field operational test. At least three conditions must be satisfied: (1) the radar and vehicle sensors must be accurate and robust; (2) data collection

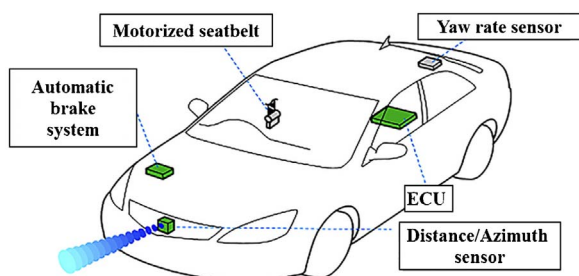


Fig. 2. System configuration of CMBS.

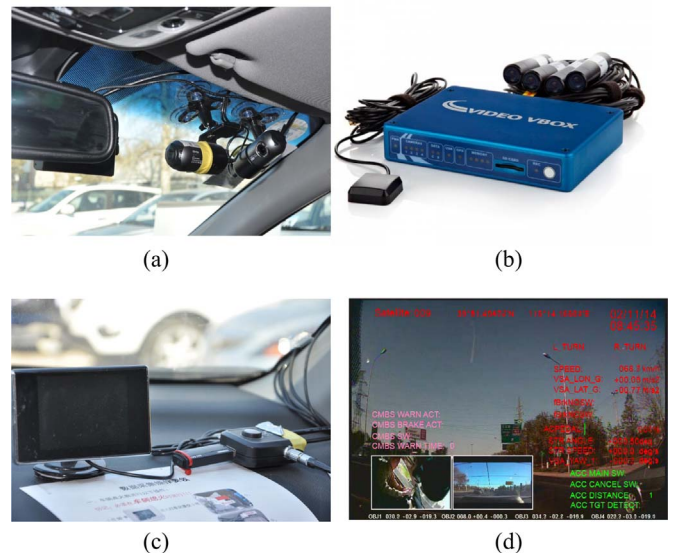


Fig. 3. (a) DRs, (b) Video VBOX, (c) Digital screen, (d) Data recording.

must be achieved in a low-intervention manner; (3) data collection must span a long testing period to record normal driving behaviors.

To collect driving data that involves the driver, CMBS, vehicle, and a real-world environment, we installed an integrated data collection system in the experiment vehicle. The data collection system consists of three driving recorders (DRs) and a set of Video VBOX, as shown in Fig. 3. The DR recorded videos of driver's operations and traffic scenes on the forward road. Video VBOX is used to export vehicle data from controller area network (CAN) bus. Also, Video VBOX is also a driving analysis tool which can be used for data recording, conservation, and playback (Vaiana et al., 2014).

With this data collection system, traffic videos, CAN data, radar information, and system signals of CMBS can be recorded. The original data include four types of signals: GPS signal (20 Hz), CMBS status signal (10 Hz), CAN signal (10 Hz) and radar signal (10 Hz). As these signals have different sampling frequency, a data synchronization process need to be conducted first, which is completed by Video VBOX. The detailed information of the four types of data are listed as follows.

- GPS signal mainly includes time, latitude, and longitude and heading angle of the vehicle.
- CMBS status signal includes the CMBS option settings, CMBS switch signal, CMBS warning status, CMBS automatic brake status, etc.
- CAN signal includes the vehicle velocity, longitudinal and lateral acceleration, brake, acceleration pedal position, steering angle and yaw rate, etc.
- The millimeter-wave radar selects four targets and measures the relative distance and relative speed between ego vehicle and the four targets.

Data collection is a continuous process (sampled in a high-frequency), but data analysis is looked at in sequence. The data extracted for analysis are interested scenarios (data sequences) which should satisfy some requirements. The method of extracting interested scenarios from the normal driving database are discussed in the following section.

2.1.2. Experiment design

We recruited 20 drivers to participate in the field operational test, including 6 female drivers and 14 male drivers. The average age was 38 years (ranging from 26 to 53). Each driver held a valid driver's licenses for an average of 12.5 years (ranging from 3 to 33 years). The driving test schedule is summarized in Table 1. Each participant drove the

Table 1
Driving test schedule.

Date	Instructions
1st Day	Be familiar with CMBS, vehicle and road
2nd Day	Driving With CMBS off
3rd Day	DrivingWith CMBS on

Table 2
Total range and duration on four types of road of the FOT.

Road type	R1	R2	R3	R4	Total
Duration (h)	78	47	159	16	300
Range (km)	6633	2460	4200	588	13880

Notation: R1 = Highway, R2 = City ring road, R3 = Inner city road, R4 = National road.

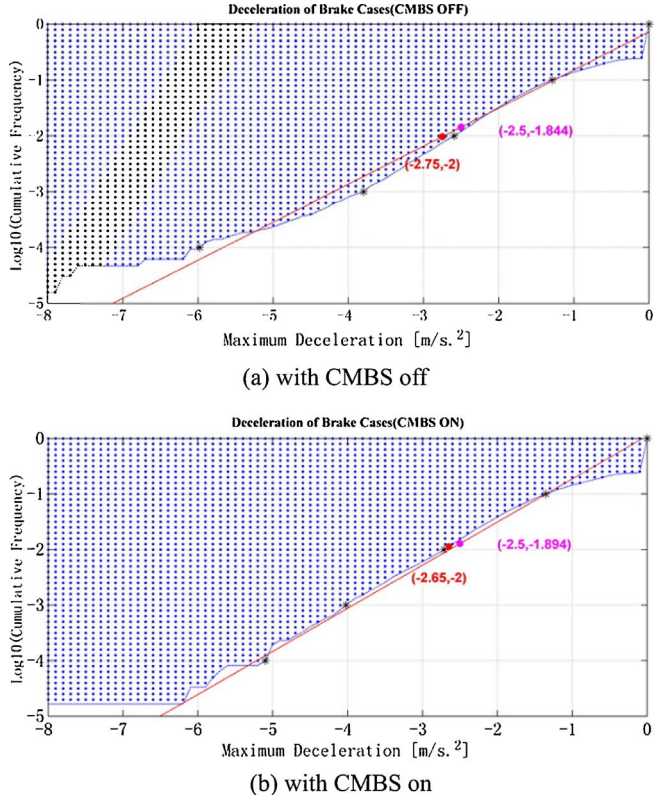


Fig. 4. Maximum deceleration with CMBS on and off.

equipped vehicle for 6–7 h/day. Participants were suggested to have at least one-hour break after two or three hours' driving test during the test period. Each driver participated the field test for three days. Within such short time, the learning or adaptation effects is not significant on the driver's intrinsic braking response characteristics (Hjälmdahl and Várhelyi, 2004). We have looked at each individual drive in sequence, and find no significant progressive changes in maximum braking deceleration with CMBS on and off (see Fig. 4). On the first day of each test, driver is required to get used to the vehicle, CMBS system and experimental route as much as possible. Over the next two days, the drivers experienced two test conditions—with CMBS off (deactivation) and with CMBS on (activation).

The experimental route included four types of roads, i.e., highway (with speed greater than 90 km/h), city ring road (mostly structured with speed of 60–80 km/h, a slight congestion), inner-city road (speed limited to under 60 km/h, mixed with pedestrians, bicycles, and motorcycles, congestion), and national road (speed of 60–80 km/h, mixed with pedestrians, bicycles, and motorcycles, some congestion), as shown in Table 2. The entire experiment lasted for 60 days. The entire field operational test covered approximately 300 h and 13,880 km in total.

2.2. Quantification of driver hazard perception

Driver hazard perception enables drivers to detect collision risks in complicated traffic environments. Thus, driver hazard perception

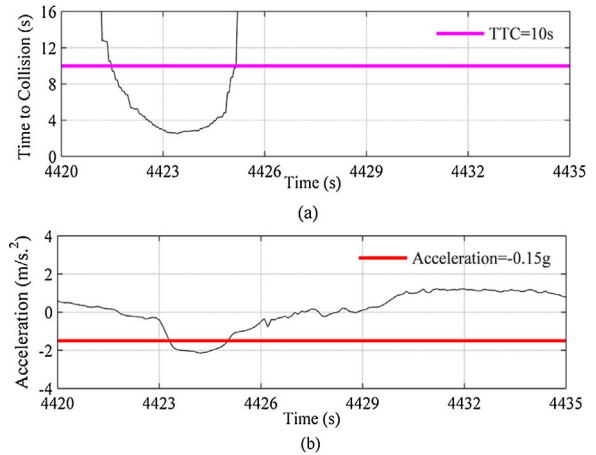


Fig. 5. TTC and acceleration of a near-crash scenario.

affects driver decision making in near-crash scenarios. It is shown that driver braking behavior in near-crash scenarios is highly related to the notion of TTC (Kaempchen et al., 2009; Montgomery et al., 2014). Usually, TTC drops below 10 s level shortly before a severe braking is activated (Lee and Peng, 2005), as shown in Fig. 5. Also, we analyzed the TTC distribution for the braking cases in our normal driving database (see Fig. 6). It is found that braking cases with TTC that is smaller than 10 s account for 95% of braking cases in which there exists a potential collision risk.

As illustrated in Fig. 7, we consider a typical near-crash scenario with a driver braking as an example. TTC – t plot falls steeply once TTC is less than 10 s. About one second later, driver applies braking and then TTC begins to rise to the safety level because of the timely braking. We can see that the TTC – t plot reveals how driving risk varies with time and how collision risk is reduced by driver braking. Based on the TTC-t plot, we introduce the definition of driver hazard perception.

Definition 1. Driver hazard perception is defined as the time elapsed between the moment when $TTC = 10$ s and the moment when the driver starts to braking, as shown in (1)

$$t_d = T_b - T_c \tag{1}$$

where t_d denotes driver risk response time, T_b denotes the moment

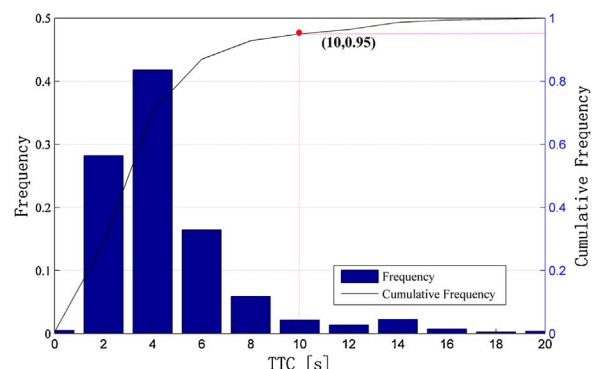


Fig. 6. TTC distribution among all braking cases.

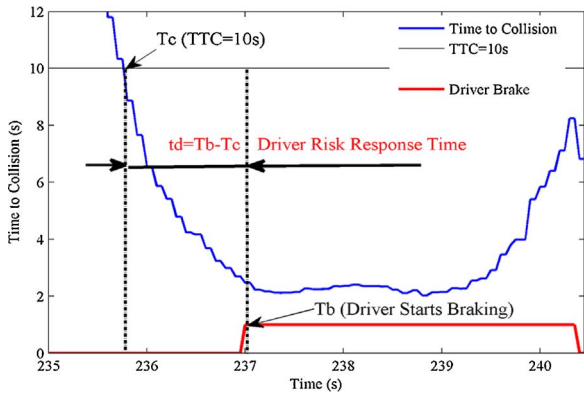


Fig. 7. Illustration of driver risk response time in TTC-t plot.

when driver starts braking, and T_c denotes the moment when TTC equals to 10 s (see Fig. 7).

The notion of driver risk response time proposed in this paper is actually a quantitative index for the measure of driver’s ability of hazard perception. It is defined using the TTC-t curve and driver braking response in a near-crash scenario. As braking cases with TTC that is smaller than 10 s account for nearly 95% of all braking cases (see Fig. 6), driver risk response time is defined as the time elapsed from the moment when $TTC = 10$ s to the moment when the driver brakes. The slope of near-crash TTC curve reflects the change rate of driving risk. Usually, if there is a high slope of TTC-t curve in the braking case, driver would make braking response as soon as possible so as to reduce the potential collision risk. From this perspective, the proposed driver risk response time is able to reflect driver’s hazard perception.

2.2.1. Near-crash scenario extraction

In this study, the measure of driver hazard perception, namely driver risk response time, is defined to quantify driver’s ability of detecting potential collision risk. The ability of hazard perception is usually related with the braking response when facing a potential collisions risk. It has been shown that driver’s braking response is affected by FCATs (Shutko, 1999; Wada et al., 2010; Wege et al., 2013; Ruscio et al., 2015). Therefore, it is assumed that the proposed driver risk response time would be influenced by CMBS. Then, by comparing the driver risk response time with CMBS activation and deactivation, we could analyze the safety effects of CMBS in terms of driver’s ability of detecting potential collision risk. As driver risk response time is defined in the special near-crash scenario, near-crash scenarios need to be extracted. It should be noted that not the number of near-crash scenarios but the driver risk response time in near-crash scenarios is compared. There are three steps for the extraction of interested near-crash scenarios.

Step 1: TTC-t plot

Since driver risk response time is defined based on a specified time trajectory of TTC, the near-crash scenario is required to possess a TTC-t plot that is similar to Figs. 4 and 7. It means, there should appear a trough in TTC-t plot of the near-crash scenario. When TTC drops below a level of 10 s, a strong braking is activated at some point to reduce the potential collision risk, making TTC gradually rise to a safe level since then.

Step 2: Effective Braking Maneuver

For an effective braking response, the driver risk response time should be less than 5 s. In addition, near-crashes with moderate-risk level have an average deceleration of 0.17 g (). Thus, to extract more near-crashes with potential collision risk beyond moderate level, we set the threshold as 0.15 g. This is described using (2):

$$\begin{cases} 0 \leq t_d \leq 5s \\ a_m \geq 0.15g \end{cases} \quad (2)$$

where a_m denotes the maximum deceleration.

Step 3: Critical Scenario

To figure out the safety effects of CMBS in near-crash scenario, near-crash scenarios with CMBS on and off are extracted for comparative analysis. Thus, those near-crash scenarios which are critical enough to trigger the CMBS warning signal are needed. For the near-crash scenario with CMBS on, if CMBS has triggered a warning signal, then the near-crash scenario can be determined to be the critical scenario. However, for near-crash scenario that occurred in condition under which CMBS was deactivated, whether it was critical enough to trigger a CMBS warning cannot easily to determine. Instead, in this study, we adopted a TTC-based CMBS warning logic for screening the critical near-crash scenarios with CMBS off. The TTC-based CMBS warning logic has been discussed in our previous conference paper (Li et al., 2016).

In all, there are three steps for the extraction of interested near-crash scenarios: (1) TTC-t plot, (2) effective braking maneuver and (3) critical scenario. In our analysis, not all the cases with TTC lower than 10 s are considered. Also, there are no requirements on the minimum TTC or the rate of change of TTC. The interested near-crash scenario is required to possess a TTC-t plot with specified characteristics. An effective braking (with maximum deceleration more than 0.15 g) is required to be applied within 5 s after TTC is lower than 10 s. Further, the near-crash scenario is required to be critical enough to trigger the CMBS warning. According to the three steps above, near-crash scenarios with CMBS on and off are extracted respectively from the driving database.

2.2.2. Driver risk response time

Based on extracted near-crash scenarios with CMBS on and off, we can calculate driver risk response time, as shown in Table 3. Driver risk response time with CMBS off and on are denoted as $t_d(2^{nd})$ and $t_d(3^{rd})$ respectively. Driver risk response time t_d varies greatly with the ego vehicle speed, ranging between [15 km/h, 90 km/h]. Here, we divided the ego vehicle speed into four ranges (see Table 3).

From Table 3, the average value of driver risk response time is reduced from 1.17 s to 0.82 s (30% reduction) due to the employment of CMBS, comparing with 24% in the earlier research (Shutko, 1999). Therefore, there exists an increase in driver hazard perception, which is contributed by the usage of CMBS. The standard deviation of the driver risk response time is reduced slightly from 0.14 s to 0.13 s. Thus, it can be concluded that CMBS makes driver hazard perception faster and more stable. More precisely, we illustrate the driver risk response time using TTC-t plot in Fig. 8. In particular, the curves are cut from the moment when $TTC = 10$ s. Driver braking points are average values of all near-crashes. According to the definition of driver risk response time, the abscissas of braking points exactly denote driver risk response time. It is shown that driver braking with CMBS on is faster than that with CMBS off. Moreover, the value of TTC at driver braking points (4 s) is close to the value of TTC when CMBS initiated warning signals (4.5 s). That is, CMBS warning is relatively consistent with driver’s hazard perception. This indicates that the CMBS warning timing implemented in our experiment vehicle is effective.

Table 3
Driver risk response time in four speed ranges.

S_i ($i = 1, 2, 3, 4$) [km/h]	t_d (2nd)[s]	t_d (3rd) [s]
	CMBS off	CMBS on
[15,30]	0.87	0.53
[30,45]	1.11	0.83
[45,60]	1.18	0.75
[60,90]	1.53	1.15
Average	1.17	0.82
Standard Deviation	0.14	0.13

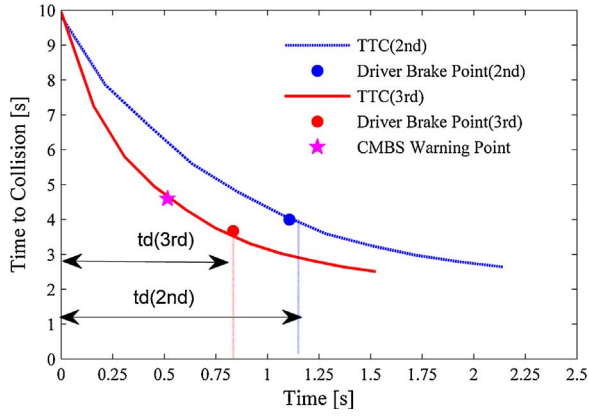


Fig. 8. Comparison of driver risk response time with CMBS on and off.

3. Crash probability estimation approach

In this section, we propose a crash probability estimation approach that considers driver risk response time, which involves three steps: 1) build a typical rear-end crash model that considers driver risk response time; 2) conduct numerical simulations on the rear-end crash model; 3) establish a crash probability estimation model.

3.1. Typical rear-end crash model

For a typical rear-end crash scenario, there usually exists short headway or distance between the leading vehicle and the following vehicle under the initial condition. If the leading vehicle decelerates immediately at a stronger deceleration, the following vehicle would apply braking as well to prevent the rear-end collision after a short response time. The typical rear-end crash model is illustrated in Fig. 11. The parameters used in the rear-end crash model are listed in Table 4.

According to the comparison between driver risk response time and the remaining collision time, the rear-end crash model can be divided into two kinds of scenarios, no braking scenario and braking scenario, as shown in Fig. 9.

- No braking scenario

If driver risk response time t_d is greater than the remaining collision time t_c , the ego vehicle driver would have no time to start braking before collision occurs.

- Braking scenario

If driver risk response time t_d is less than the remaining collision time t_c , the ego vehicle driver would have extra time to apply braking after driver risk response time t_d .

Table 4
Parameters used in the rear-end crash model.

Parameters	Definitions
v_s, v_t	Velocity of the subject (ego) vehicle, leading vehicle.
D_0	Initial distance (range) between two vehicles
a_s, a_t	Deceleration of the ego vehicle, leading vehicle
v_r	Relative speed when collision occurs ($v_r = v_s - v_t$)
v_c	Critical speed
t_d	Driver risk response time
t_c	The moment when collision occurs.
$THW_{initial}$	Initial time headway (THW)
$TTC_{initial}$	Initial time to collision (TTC)

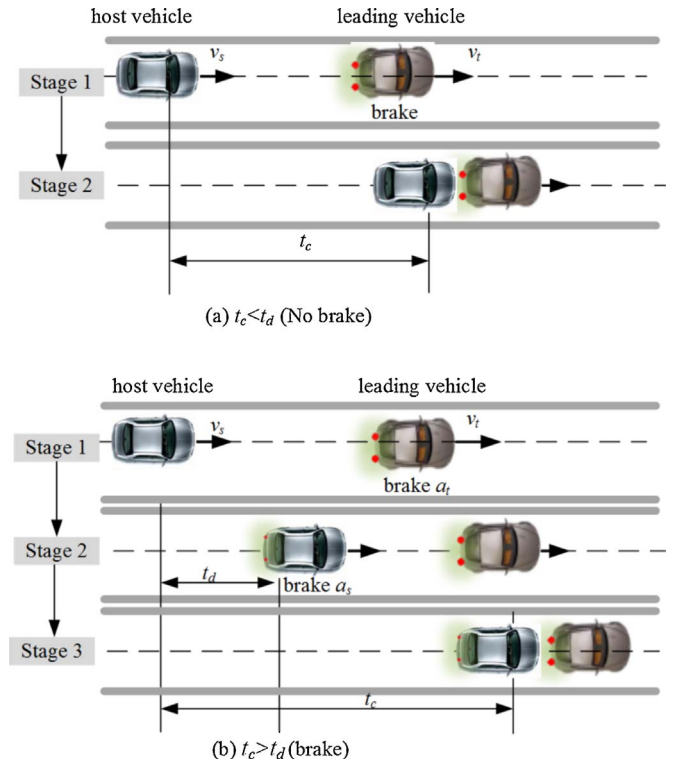


Fig. 9. Typical rear-end crash model, (a) no braking scenario and (b) braking scenario.

3.1.1. No braking scenario

As shown in Fig. 8(a), the leading vehicle decelerates at a constant rate a_t and the ego vehicle maintains the initial speed v_s during the entire process. We describe this scenario using motion equation as follows.

$$v_s t_c = D_0 + v_t t_c - \frac{1}{2} a_t t_c^2 \quad (3)$$

The collision moment t_c can be solved using Eq. (3). By substituting t_c into Eq. (4), we can calculate the relative speed v_r at the moment of collision.

$$v_r = v_s - (v_t - a_t t_c) \quad (4)$$

The condition that guarantees the existence of a real solution is given below (5).

$$\begin{cases} \Delta = (v_t - v_s)^2 + 2D_0 a_t \geq 0 \\ t_c = -\frac{(v_s - v_t) - \sqrt{\Delta}}{a_t} < t_d \end{cases} \quad (5)$$

Eq. (5) guarantees the existence of a real solution.

3.1.2. Braking scenario

As shown in Fig. 8(b), the leading vehicle decelerates at a constant rate a_t . The ego vehicle maintains a constant speed v_s throughout the response time t_d and then decelerates at a constant rate a_s until collision occurs. We describe this scenario using motion equation as follows (6)

$$v_s t_c - \frac{1}{2} a_s (t_c - t_d)^2 = D_0 + v_t t_c - a_t t_c^2 \quad (6)$$

The moment of collision t_c can be determined by solving (6). By substituting t_c into (7), we can calculate the relative speed v_r at the moment of collision.

$$v_r = v_s - a_s t_c + a_s t_d - v_t + a_t t_c \quad (7)$$

The condition that guarantees the existence of a real solution is given below (8).

$$\begin{cases} \Delta = (v_t - v_s - a_s t_d)^2 - 2(a_s - a_t)(D_0 + \frac{1}{2}a_s t_d^2) \geq 0 \\ t_c = \min \left\{ \frac{-(v_t - v_s - a_s t_d)^2 + \sqrt{\Delta}}{a_s - a_t} > t_d \right\} \end{cases} \quad (8)$$

Then, relative speed v_r can be expressed as a quadratic function of host vehicle speed v_s as

$$v_r = (a_t - a_s) \cdot \frac{-(v_t - v_s - a_s t_d)^2 + \sqrt{\Delta}}{a_s - a_t} + v_s + a_s t_d - v_t \quad (9)$$

3.2. Numerical simulation

Numerical simulations are used to study the behavior of systems when the mathematical models are too complex to derive analytical solutions. In this study, to explore the relationship between crash probability and driver hazard perception, numerical simulations of the rear-end crash model are employed.

3.2.1. Simulation

Simulation parameters for the typical rear-end model are described as follows:

- Initial time-to collision $TTC_{initial} = 10$ s. Driver risk response time is defined as the time elapsed from the moment when $TTC = 10$ s to the moment when driver starts braking. If we set $TTC_{initial} = 10$ s, driver risk response time can be exactly represented with the brake response time.
- Initial time headway $THW_{initial} = 2$ s. THW on condition that TTC equals to 10 s of all near-crash scenarios is shown in Fig. 10. It can be seen that near-crash scenarios with THW less than 2 s accounts for 92% of all near-crash scenarios on condition that $TTC = 10$ s. Thus, $THW = 2$ s on condition that $TTC = 10$ s could include about 92% of near-crash scenarios.
- Initial speed of ego vehicle $v_s = [0, 100]$ km/h.
- Initial gap $D_0 = v_s * THW_{initial}$.
- Initial speed of leading vehicle $v_t = v_s - \frac{D_0}{TTC_{initial}}$.
- Longitudinal deceleration of ego vehicle $a_s = 0.4$ g and that of leading vehicle $a_t = 0.2$ g.

The higher relative speed at collision moment usually results in much more severe injuries (Otte et al., 2012). Thus, by studying how the relative speed at the collision moment varies with driver risk response time, we can establish a relationship between collision risk and driver risk response time. We set the driver risk response times as $t_d = 1.5$ s, 2.0 s, and 2.5 s, respectively. Fig. 11 shows the simulation results. The horizontal axis denotes the ego vehicle speed v_s and the vertical axis denotes the relative speed v_r at the collision moment. Results indicate that the relative speed at collision moments v_r is the

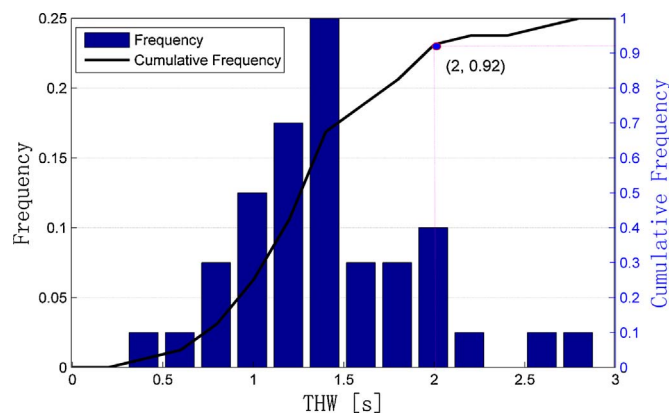


Fig. 10. THW distribution on condition that $TTC = 10$ s for all near-crash scenarios.

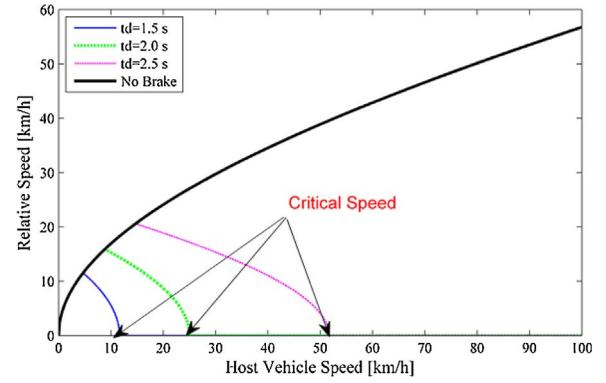


Fig. 11. Simulation results with driver risk response times as $t_d = 1.5$ s, 2.0 s, and 2.5 s, respectively.

quadratic function of host vehicle speed v_s . These quadratic curves between relative speed and host vehicle speed are exactly consistent with Eq. (9), showing the validity of the numerical simulations. Moreover, from Fig. 11, we have the following findings.

- If the ego vehicle does not apply braking during the entire process (see dark curve), the relative speed at the collision moment would increase monotonically with ego vehicle speed. In this case, collision occurs all the time.
- If the ego vehicle brakes, the relative speed at the collision moment would first increase to a maximum point and finally decrease to zero, going into collision-free region.
- Comparing three curves ($t_d = 1.5$ s, 2.0 s and 2.5 s), it is clear that relative speed at the collision moment increases with driver risk response time, signifying that collision risk increases with driver risk response time as well.

We define the cross points of the three curves with the horizontal axis as critical speed, which is denoted as v_c . As depicted in Fig. 11, if ego vehicle speed is lower than critical speed, the collision always occurs (the relative speed at collision moment is greater than zero). In contrast, if ego vehicle speed is greater than critical speed, there is no collision (the relative speed at collision moment is zero). Therefore, critical speed could be considered as the boundary of collision and collision-free region for a given ego vehicle speed. We arrived at the following decision rules for collision:

- If $v_s < v_c$, the collision occurs
- If $v_s > v_c$, there is no collision

3.2.2. Critical speed

For each value of driver risk response time, we can calculate the critical speed. Thus, to determine the relationship between critical speed and driver risk response time, we conducted simulations with driver risk response time ranging from 0.2 s to 2.5 s (simulation step is 0.1 s), as shown in Fig. 12(a). After that, we fitted the relationship between driver risk response time and critical speed onto a quadratic curve, as shown in Fig. 12(b). The curve equation can be expressed as below (10):

$$v_c = 12.6t_d^2 - 13.9t_d + 4.5 \quad (10)$$

where v_c denotes the critical speed and t_d denotes the driver risk response time.

3.3. Crash probability estimation model

As discussed previously, collision risk can be connected with driver risk response time based on the relationship between critical speed v_c and driver risk response time t_d (see Eq. (10)). Thus, the crash

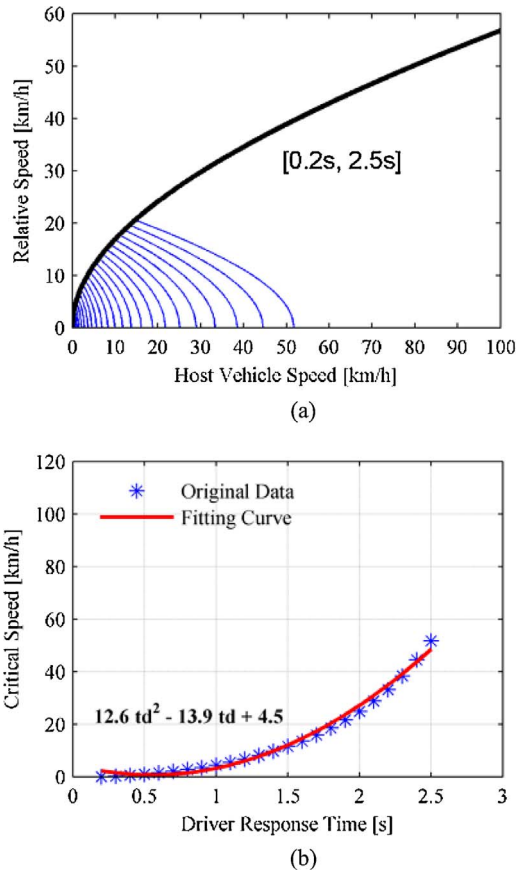


Fig. 12. (a) Numerical simulations with driver risk response time t_d ranging between 1.5 s and 2.5 s. (b) Quadratic relationship between critical speed and risk response time.

probability estimation model can be described in (10) as follows:

$$\begin{cases} v_c^{S_i} = f(t_d^{S_i}) \\ CP_{crash} = \sum_{i=1}^N P(v < v_c^{S_i} | S_i) P(S_i) \end{cases} \quad (11)$$

where $S_i (i = 1, 2, \dots, N)$ denotes speed ranges, $t_d^{S_i}$ denotes driver risk response time in speed range S_i ; $v_c^{S_i}$ denotes the critical speed in each speed range S_i , which can be calculated using (10); $P(S_i)$ denotes the probability of speed being distributed in the speed range S_i ; $P(v < v_c^{S_i} | S_i)$ denotes the probability (conditional crash probability) of S_i speed that is lower than critical speed in the speed range

According to the law of total probability (Schervish, 2012), we can calculate the overall crash probability CP_{crash} .

In this model, $P(S_i)$ can be ascertained based on the driving database from field operational test. If the host vehicle speed v is less than the critical speed $v_c^{S_i}$ for a given speed range S_i , the collision occurs (*i.e.*, conditional crash probability $P(v < v_c^{S_i} | S_i)$ is 100%). Note that the proposed crash probability estimation approach explicitly accounts for driver hazard perception ability, which is able to predict the crash probability of a near-crash scenario in a more practical way. Predicting the crash probability is essential during the development and testing stage of the collision avoidance technologies. The crash probability estimation approach can predict the potential collision avoidance performance of FCATs based on real-world driving with both driver and collision avoidance system in the loop. Thus, it is helpful to employ this approach to evaluate the practical crash reduction effects of the collision avoidance systems in the real-world driving environment.

4. Approach validation

To validate the proposed crash probability estimation approach, we calculate the crash probability with CMBS on and off based on the driving database from field operational test, which helps determine the crash probability reduction contributed by CMBS. If crash probability is reduced with the assistance of CMBS, which is consistent with the designed CMBS function, the proposed crash probability estimation approach would be proved effective.

4.1. Preparations for crash probability estimation

Drivers were required to operate the experiment vehicle following the traffic rules for safety concerns in our experiment test. Any traffic violation behaviors, such as speeding and alcohol driving, are not allowed in the field test. Therefore, driver risk response time that is calculated from the normal driving database is usually enough to prevent collisions. In other words, those near-crash scenarios which are extracted from the driving database are not critical enough to show the significant effects of CMBS.

Distraction has been identified as a primary contributor to rear-end collisions (Wege et al., 2013). Usually, if a driver is distracted, the driver risk response time would be delayed. Based on the public 100-car and 8-truck naturalistic data from VTTI, it is shown that driver distraction and inattention contribute to 80% of traffic accidents by delaying or hindering driver responses (Klauer et al., 2006). Research shows that driver's eye glances away from the road range from 0.7 s to slightly over 1 s (Kircher, 2007). Therefore, we add one-second delay to driver risk response time to calculate the potential safety effects of CMBS. According to equation (10), we then recalculate the critical speed with CMBS off and on if there exists a one-second delay of driver's braking response, which are denoted as v_c^{2nd} and v_c^{3rd} , as shown in Table 5 below. After acquiring critical speed, we then calculate speed distributions based on the field operational test to calculate the conditional crash probability. The speed distribution frequency with CMBS off and on, which are denoted as $P^{2nd}(S_i)$ and $P^{3rd}(S_i)$, are summarized in Table 6. Based on the speed distribution and critical speed, the conditional crash probability with CMBS off and on can be represented with cumulative frequency of critical speed in the corresponding speed range, which are denoted as $P(v < v_c^{2nd} | S_i)$ and $P(v < v_c^{3rd} | S_i)$ respectively. In the simulation, we add one-second time delay on driver risk response time to calculate the potential safety effects of CMBS.

The conditional crash probability under normal condition and time-delay condition are shown in Tables 7 and 8 respectively. Both the crash probability with CMBS on and off under normal condition is nearly zero in all speed ranges (see Table 7), which means drivers are usually able to avoid crashes when they are not delayed. However, there is a significant reduction in crash probability with CMBS on during the speed range from 15 km/h to 45 km/h if there exists a one-second delay in driver's braking response (see Table 8). The response speed of radar of CMBS is usually not fast enough for the real-time target detection at high speed range. Thus, CMBS is mainly designed to address rear-end accidents in low speed range on inner city road. This simulation result is exactly consistent with the expectation of CMBS. It can be seen that the CMBS is more effective in low speed under time-delay condition.

Table 5
Critical speed in each speed range if there exists a one-second delay of driver's braking response.

$S_i (i = 1, 2, 3, 4)$ [km/h]	v_c^{2nd} [km/h] CMBS off	v_c^{3rd} [km/h] CMBS on
[15,30]	22.6	12.7
[30,45]	31.3	21.3
[45,60]	34.1	18.8
[60,90]	50.0	32.9

Table 6
Speed distribution from the field operational test.

S_i ($i = 1, 2, 3, 4$) [km/h]	$p^{2nd}(S_i)$ CMBS off	$p^{3rd}(S_i)$ CMBS on
[15,30]	0.258	0.262
[30,45]	0.267	0.258
[45,60]	0.204	0.211
[60,90]	0.260	0.261

Table 7
Conditional crash probability in each speed range under normal condition.

S_i ($i = 1, 2, 3, 4$) [km/h]	$P(v < v_c^{2nd} S_i)$ CMBS off	$P(v < v_c^{3rd} S_i)$ CMBS on
[15,30]	0	0
[30,45]	0	0
[45,60]	0	0
[60,90]	0	0

Table 8
Conditional crash probability in each speed range under time-delay condition.

S_i ($i = 1, 2, 3, 4$) [km/h]	$P(v < v_c^{2nd} S_i)$ CMBS off	$P(v < v_c^{3rd} S_i)$ CMBS on
[15,30]	0.48	0
[30,45]	0.11	0
[45,60]	0	0
[60,90]	0	0

4.2. Crash probability reduction

Based on the speed probability and conditional crash probability in each speed ranges, the overall crash probability with CMBS off and on, which are denoted as CP_{crash}^{2nd} and CP_{crash}^{3rd} respectively, can be calculated. According to Eq. (11), $CP_{crash}^{2nd} = 15.32\%$, $CP_{crash}^{3rd} = 0$. That is, the crash probability is reduced to zero with CMBS on. Considering that the simulation scenario with $THW < 2$ s and $TTC = 10$ s accounts for nearly 92% of all near-crashes. Also, nuisance alarms account for less than 2% (3/152) of all alarms cases in this field operational test. Thus, the overall crash probability reduction contributed by CMBS under the condition that the driver has one-second delay of braking response is written as: $15.3\% \cdot 92\% \cdot (1 - 2\%) = 13.7\%$. It is concluded that CMBS is positive in collision avoidance for near-crashes characterized by driver's braking response delay. This result indicates that the proposed crash probability estimation approach is effective.

5. Discussion

In our study, we propose a practical crash probability estimation method and evaluate the safety performance of CMBS based on a field operational test. A few topics remain worth investigation to further reinforce and validate the proposed crash probability estimation approach.

First, a CMBS-equipped vehicle is used to record the participants' driving behavior on a specific routes for 6–7 h per day. During our data collection, participants are suggested to have at least one-hour break after 2 or 3 h' driving during the test period. In fact, driving 6–7 h in one day is unusual for normal drivers even for professional drivers. The long-duration driving may lead to the drowsy driving which might make the experimental data biased. Thus, to avoid the unexpected behavior of drowsy driving, driving less than 3 h in one day may be more appropriate for normal drivers.

Second, it is necessary for naturalistic driving tests to last enough time for participants, such that they become unaware that their driving

behavior is being monitored and the learning or adaptation behavior effects are reduced. This study proposes a crash probability estimation model via quantifying driver's hazard perception. To validate this model, a two-month field operational test based on the CMBS-equipped vehicle is conducted. Near-crash scenarios with and without CMBS are extracted respectively for calculating driver hazard perception measure (driver risk response time). CMBS effects on crash probability is finally calculated based on comparison of driver's risk response time in near-crash scenarios with/without CMBS. In our experiment, each driver participated the field test for three days. Within such short time, the learning or adaptation effects is not significant on the driver's intrinsic braking response characteristics (Hjälmdahl and Várhelyi, 2004). In addition, we have looked at each individual drive in sequence, and find no significant progressive changes in maximum braking deceleration (see Fig. 4). Therefore, our analysis results are valid for analyzing the effects of CMBS. However, it is still necessary to check that the changes in driver risk response time are actually due to the CMBS intervention rather than learning or adaptation effects while performing CMBS on/off experiments. It would be better to conduct a long-term field test (e.g., one or two months) for each driver, such that they get used to the experiment vehicle and road condition, meaning that the learning or adaption of the driver become stable. Also, individual driving should be looked at in sequence and analyzed for the learning or adaptation effects on driver's behavior characteristics. Then, we start the controlled experiment when the learning or adaptation effects is negligible, which would make the results more reliable. Then, data on a greater number of near-crashes could be collected by conducting longer driving tests.

Finally, further validation using near-crash scenarios in different traffic environments will be helpful to strengthen accuracy of the proposed approach. Real-world traffic environments actually involve different features in different driving contexts (Zheng et al., 2014). Also, more robust and all-weather radar sensors contribute to generating more available driving dataset. Finally, driver's evasive steering responses to the warnings of collision avoidance technologies are also essential (Keller et al., 2011). In our field operational test, as driver's evasive steering responses to CMBS warning account for less than 5% of all warning cases, we ignored the crash reduction effect contributed by driver steering response. In future, if a larger database becomes available, it is necessary to consider driver's evasive steering responses to system warnings. Moreover, as there was no case that triggered CMBS braking function, the final effect results from CMBS warning function.

6. Conclusion

This paper proposed a practical approach to estimate crash probability of a typical rear-end scenario considering driver hazard perception. The purposes of this study can be summarized in two aspects: 1) proposed a method to estimate the crash probability in the rear-end collision scenario and 2) validating this method in evaluating the crash avoidance effect of a forward collision avoidance technology through a field operational test and numerical simulations.

The driver's ability of hazard perception is viewed as an important factor for crash avoidance. The proposed crash probability estimation approach of this study has the potential to expand our understandings of driver hazard perception ability and its effect on the crash avoidance performance of collision avoidance technologies. First, a novel driver hazard perception measure, namely, driver risk response time, was quantified based on the time trajectory of TTC and the driver's braking response in a near-crash scenario. The average reduction of driver risk response time with the assistance of the CMBS is as much as 30%, which is consistent with the expected function of CMBS. Second, we consider the driver hazard perception measure while establishing the typical rear-end crash model. Through numerical simulations, we establish the relationship between collision risk and driver hazard perception measure. Finally, by combining the numerical simulations and normal driving database, we figure out the crash probability. Result shows with

a one-second delay of driver's braking response, a 13.7% reduction in rear-end crash probability was achieved with CMBS on. This reduction in crash probability shows the considerable collision avoidance effect of CMBS if there exists driver's braking response delay, which is in line with the design concept of CMBS.

By taking driver hazard perception into account, this crash probability estimation approach can predict the crash probability of a near-crash scenario in a more practical way. Moreover, this approach is effective in safety effect evaluation of collision avoidance systems during the design and testing stages. For instance, aging drivers or retarded drivers with poor hazard perception ability, the warning timing of collision avoidance systems can be adjusted to achieve the maximum crash probability reduction effect.

Acknowledgments

This research was supported by National Natural Science Foundation of China (Grant No. 51475254 and No. 51625503) and the joint project of Tsinghua and Honda. The work of Y. Zheng is supported by the Clarendon Scholarship and the Jason Hu Scholarship. The authors would like to the Editor and the anonymous reviewers for their valuable comments that helped us improve the quality of the manuscript.

References

- Benmimoun, M., Pütz, A., Zlocki, A., Eckstein, L., 2013. euroFOT: field operational test and impact assessment of advanced driver assistance systems: final results. Proceedings of the FISITA 2012 World Automotive Congress 537–547.
- Borowsky, A., Oron-Gilad, T., Meir, A., Parmet, Y., 2012. Drivers' perception of vulnerable road users: a hazard perception approach. *Accid. Anal. Prev.* 44 (1), 160–166.
- Chin, H.C., Quek, S.T., 1997. Measurement of traffic conflicts. *Saf. Sci.* 26 (3), 169–185.
- Crundall, D., Chapman, P., Trawley, S., Collins, L., Van Loon, E., Andrews, B., Underwood, G., 2012. Some hazards are more attractive than others: drivers of varying experience respond differently to different types of hazard. *Accid. Anal. Prev.* 45, 600–609.
- Dingus, T.A., Klauer, S.G., Neale, V.L., Petersen, A., Lee, S.E., Sudweeks, J.D., Bucher, C., et al., 2006. The 100-car Naturalistic Driving Study, Phase II-Results of the 100-Car Field Experiment (No. HS-810 593).
- Distner, M., Bengtsson, M., Broberg, T., Jakobsson, L., 2009. City safety—a system addressing rear-end collisions at low speeds. Proc. 21st International Technical Conference on the Enhanced Safety of Vehicles (No. 09-0371).
- Dozza, M., 2013. What factors influence drivers' response time for evasive maneuvers in real traffic? *Accid. Anal. Prev.* 58, 299–308.
- Fildes, B., Keall, M., Bos, N., Lie, A., Page, Y., Pastor, C., et al., 2015. Effectiveness of low speed autonomous emergency braking in real-world rear-end crashes. *Accid. Anal. Prev.* 81, 24–29.
- Georgi, A., Zimmermann, M., Lich, T., Blank, L., Kickler, N., Marchthaler, R., 2009. New approach of accident benefit analysis for rear end collision avoidance and mitigation systems. 21st International Technical Conference on the Enhanced Safety of Vehicles.
- Guo, F., 2010. Near-crashes as crash surrogate for naturalistic driving studies. *Transp. Res. Rec. J. Transp. Res. Board* 2147 (–1), 66–74.
- Hjälmdahl, M., Várhelyi, A., 2004. Speed regulation by in-car active accelerator pedal: effects on driver behaviour. *Transp. Res. Part F: Traffic Psychol. Behav.* 7 (2), 77–94.
- Källhammer, J.E., Smith, K., Matsangas, P., 2016. Modeling ratings of in-vehicle alerts to pedestrian by leveraging field operational tests data in a controlled laboratory study. *Transp. Res. Part F: Traffic Psychol. Behav.* 45, 413–425.
- Kaempchen, N., Schiele, B., Dietmayer, K., 2009. Situation assessment of an autonomous emergency brake for arbitrary vehicle-to-vehicle collision scenarios. *IEEE Trans. Intell. Transp. Syst.* 10 (4), 678–687.
- Keller, C.G., Dang, T., Fritz, H., Joos, A., Rabe, C., Gavrilu, D.M., 2011. Active pedestrian safety by automatic braking and evasive steering. *IEEE Trans. Intell. Transp. Syst.* 12 (4), 1292–1304.
- Kircher, K., 2007. Driver Distraction: A Review of the Literature.
- Klauer, S.G., Dingus, T.A., Neale, V.L., Sudweeks, J.D., Ramsey, D.J., 2006. The Impact of Driver Inattention on Near-crash/crash Risk: An Analysis Using the 100-car Naturalistic Driving Study Data.
- Kusano, K.D., Gabler, H.C., 2012. Safety benefits of forward collision warning, brake assist, and autonomous braking systems in rear-end collisions. *IEEE Trans. Intell. Transp. Syst.* 13 (4), 1546–1555.
- Lee, K., Peng, H., 2005. Evaluation of automotive forward collision warning and collision avoidance algorithms. *Veh. Syst. Dyn.* 43 (10), 735–751.
- Li, Y., Zheng, Y., Wang, J., Wang, L., Kodaka, K., Li, K., 2016. Evaluation of Forward Collision Avoidance system using driver's hazard perception. 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC) 2273–2278.
- Markkula, G., Engström, J., Lodin, J., Bårgman, J., Victor, T., 2016. A farewell to brake reaction times? kinematics-dependent brake response in naturalistic rear-end emergencies. *Accid. Anal. Prev.* 95 (Pt. A), 209–226.
- McLaughlin, S.B., Hankey, J.M., Dingus, T.A., 2008. A method for evaluating collision avoidance systems using naturalistic driving data. *Accid. Anal. Prev.* 40 (1), 8–16.
- Meir, A., Borowsky, A., Oron-Gilad, T., 2014. Formation and evaluation of Act and Anticipate Hazard Perception Training (AAHPT) intervention for young novice drivers. *Traffic Inj. Prev.* 15 (2), 172–180.
- Montgomery, J., Kusano, K.D., Gabler, H.C., 2014. Age and gender differences in time to collision at braking from the 100-car naturalistic driving study. *Traffic Inj. Prev.* 15 (suppl. 1), S15–S20.
- National Highway Traffic Safety Administration, 2014. National Automotive Sampling System—Crashworthiness Data System: 2012 Analytical User's Manual. US Department of Transportation, Washington, DC.
- Neale, V.L., Dingus, T.A., Klauer, S.G., Sudweeks, J., Goodman, M., 2005. An Overview of the 100-car Naturalistic Study and Findings. National Highway Traffic Safety Administration, Paperpp. 05–0400.
- Nodine, E.E., Lam, A.H., Najm, W.G., Ference, J.J., 2011. Safety Impact of an Integrated Crash Warning System Based on Field Test Data. 22nd ESV.
- Otte, D., Jänsch, M., Haasper, C., 2012. Injury protection and accident causation parameters for vulnerable road users based on german in-depth accident study gidas. *Accid. Anal. Prev.* 44 (1), 149–153.
- Ruscio, D., Ciceri, M.R., Biassoni, F., 2015. How does a collision warning system shape driver's brake response time? The influence of expectancy and automation complacency on real-life emergency braking. *Accid. Anal. Prev.* 77, 72–81.
- Sagberg, F., Bjørnskau, T., 2006. Hazard perception and driving experience among novice drivers. *Accid. Anal. Prev.* 38 (2), 407–414.
- Schervish, M.J., 2012. Theory of Statistics. Springer Science & Business Media.
- Shutko, J., 1999. An Investigation of Collision Avoidance Warnings on Brake Response Times of Commercial Motor Vehicle Drivers (Doctoral Dissertation). Virginia Polytechnic Institute and State University.
- Traffic Administration Bureau of the Ministry of Public Security of PRC, 2012. China Road Traffic Accidents Statistics. Beijing, China.
- Vaiana, R., Iuele, T., Astarita, V., Caruso, M.V., Tassitani, A., Zaffino, C., Giofrè, V.P., 2014. Driving behavior and traffic safety: an acceleration-based safety evaluation procedure for smartphones. *Mod. Appl. Sci.* 8 (1), 88.
- Wada, T., Doi, S.I., Tsuru, N., Isaji, K., Kaneko, H., 2010. Characterization of expert drivers' last-second braking and its application to a collision avoidance system. *IEEE Trans. Intell. Transp. Syst.* 11 (2), 413–422.
- Wang, J., Zheng, Y., Li, X., Yu, C., Kodaka, K., Li, K., 2015a. Driving risk assessment using near-crash database through data mining of tree-based model. *Accid. Anal. Prev.* 84, 54–64.
- Wang, J.Q., Li, S.E., Zheng, Y., Lu, X.Y., 2015b. Longitudinal collision mitigation via coordinated braking of multiple vehicles using model predictive control. *Integr. Comput.-Aided Eng.* 22 (2), 171–185.
- Wege, C., Will, S., Victor, T., 2013. Eye movement and brake reactions to real world brake-capacity forward collision warnings—a naturalistic driving study. *Accid. Anal. Prev.* 58, 259–270.
- Wu, K.F., Aguero-Valverde, J., Jovanis, P.P., 2014. Using naturalistic driving data to explore the association between traffic safety-related events and crash risk at driver level. *Accid. Anal. Prev.* 72, 210–218.
- Zellner, J., 2012. Extension of the honda-dri “safety impact methodology” (sim) for the nhtsa advanced crash avoidance technology (acat) ii program and application to the evaluation of a pre-production head-on crash avoidance assist system – progress report. *SAE Int. J. Passenger Cars-Electron. Electr. Syst.* 5 (2), 385–402.
- Zheng, Y., Wang, J., Li, X., Yu, C., Kodaka, K., Li, K., 2014. Driving risk assessment using cluster analysis based on naturalistic driving data. 17th International IEEE Conference on Intelligent Transportation Systems (ITSC) 2584–2589.