

This is a repository copy of DSRC-based rear-end collision warning system – An error-component safety distance model and field test.

White Rose Research Online URL for this paper: http://eprints.whiterose.ac.uk/149864/

Version: Accepted Version

## Article:

Zhao, X, Jing, S, Hui, F et al. (2 more authors) (2019) DSRC-based rear-end collision warning system – An error-component safety distance model and field test. Transportation Research, Part C: Emerging Technologies, 107. pp. 92-104. ISSN 0968-090X

https://doi.org/10.1016/j.trc.2019.08.002

Crown Copyright © 2019 Published by Elsevier Ltd. Licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License (http://creativecommons.org/licenses/by-nc-nd/4.0/).

#### Reuse

This article is distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs (CC BY-NC-ND) licence. This licence only allows you to download this work and share it with others as long as you credit the authors, but you can't change the article in any way or use it commercially. More information and the full terms of the licence here: https://creativecommons.org/licenses/

#### Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.



eprints@whiterose.ac.uk https://eprints.whiterose.ac.uk/

#### Please cite paper as:

Zhao, X, Jing, S, Hui, F, Liu, R and Khattak, AJ (2019) DSRC-based rear-end collision warning system – An error-component safety distance model and field test. **Transportation Research Part C.** Vol. 107, 92-104.

# DSRC-Based Rear-End Collision Warning System - An Error-component Safety Distance Model and Field Test

Xiangmo Zhao<sup>a</sup>, Shoucai Jing<sup>a\*</sup>, Fei Hui<sup>a</sup>, Ronghui Liu<sup>b</sup>, Asad J. Khattak<sup>a,c</sup>

(<sup>a</sup> School of Information Engineering, Chang'an University, Xian 710064, China

<sup>b</sup> Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, UK

<sup>c</sup>Civil and Environmental Engineering Department, University of Tennessee, Knoxvile, TN 37996 USA) **Abstract:** Dedicated short-range communication (DSRC) technology can provide drivers with information about other vehicles that are beyond the normal range of vision and enables the development of driving support systems such as the rear-end collision warning system (ReCWS). However, technology constraints such as communication delays and GPS error affect the accuracy of a DSRC-based ReCWS. This paper proposes a ReCWS design that explicitly represents functional specifications of DSRC technology, including transmission delay specifications that describe the information transmission process and an error-component safety distance specification used to represent the effect of GPS error and the information propagation delay. We propose three collision warning strategies each with different deceleration requirements. The system is assembled with off-the-shelf DSRC and mobile technology that can be readily installed into test vehicles. To test the effectiveness of the proposed ReCWS, we ran a variety of controlled scenarios on a test track. The results show a high degree of warning accuracy. These field test results also provide calibrated system parameter values for future studies and designs of DSRC-based ReCWSs.

**Keywords:** Dedicated short-range communication (DSRC); Rear-end collision warning; Transmission delay; Safety distance model; Warning strategy; V2V.

# **1. Introduction**

Although the number of traffic accidents has been decreasing year by year, casualties and economic losses are still significant. There were 35485 motor vehicle traffic fatalities where the

E-mail addresses: shoucjing@chd.edu.cn (S. Jing)

rear-end collision accidents account for more than 30% (NHTSA, 2015). Analysis of these traffic accidents suggests that they happen when drivers of following vehicles do not pay enough attention to the leading vehicle's deceleration and when following vehicles travel too closely behind (Dingus

<sup>\*</sup> Corresponding author.

E-mail addresses: shoucjing@chd.edu.cn (S. Jing)

et al., 1997). Therefore, a system that can detect and warn drivers how to decelerate to avoid the potential rear-end collisions could significantly reduce the number of accidents (Jamson et al., 2008).

There are two general approaches to developing a rear-end collision warning system (ReCWS). A traditional ReCWS uses ranging sensors (e.g. radar and camera) to detect vehicles in front of the equipped vehicle (Abdel-Aty et al., 2012; Alpar et al., 2016; Yang et al., 2015). These systems are expensive and their performance is limited because conditions such as darkness, fog and rain interfere with the detection (Rasshofer et al., 2011). The second approach uses vehicle to vehicle (V2V) communication technology which allows vehicles to exchange movement and trajectory information within their communication ranges (Hafeez et al., 2013). V2V technology can withstand adverse conditions and ensures the applicability of the system. As a result, research on ReCWSs in recent years have largely been focused on their compatibility with V2V technology.

Li et al. (2013) proposed a V2V-based ReCWS based on risk perception to identify danger. When the system detects an unsafe driving speed, it warns the driver to decelerate. Wang et al. (2015, 2016) developed a model based on the concept of driving safety field theory that considers driver-vehicle-road interactions to determine the safety field strength in detail. A study by Huang et al. (2014) analyzed a cooperative vehicle collision warning system under a variety of speeds, road conditions and GPS delays. The results show that the system has a low warning rate at intersections. Benedettoa et al. (2015) applied telecommunication methodologies for detecting hazardous driving conditions in order to avoid rear-end collisions. These experiments showed that the system had a high degree of detection with regard to small distances. With the development of communication technology, Cellular-V2X has drawn increasing attention. Vukadinovic et al. (2018) compared two families of radio technology: IEEE 802.11p and 3GPP Cellular-V2X in highway platooning scenarios. Simulation results show that C-V2X in both modes allows for shorter distances than IEEE 802.11p due to increased reliability of communication performance under increasing congestion on the wireless channel. However, there are few studies about C-V2X –based safety applications or real-life tests.

There has also been research that employs intelligent vehicle to infrastructure (V2I) communication technology for collision avoidance. Khan (2007) proposed a queue-end warning system for highway work zones that automatically predicts the location of a queue-end and alerts drivers based on intelligent infrastructure. Wang et al. (2011) proposed a vehicle trajectory collision

warning system based on V2I that employed the method of Kalman Filter to predict the vehicle trajectory. The system predicts collisions using models of time to collision (TTC) which respectively considers vehicles as particles, circles and rectangles. The above systems are good at different scenarios, but none of them takes into account the influence of information delays and GPS errors.

A critical safety distance model based on V2V communication (Chen et al., 2013) considered information transmission delay, but the method requires dividing the radio ranges into different communication zones and controls the beacon frequency according to the required message propagation. DSRC-based systems communicate by broadcasting so the emissive frequency cannot change frequently. As a result DSRC system cannot use the critical safety distance model. Xiang et al. (2014) analyzed the advantages of DSRC and established a multi-level warning system based on vehicle kinematic models and neural networks. Simulation experiments showed that the number of correct warning rates ranges from 80% to 95%. This system did not model the information transmission process, so the experiment only provided a maximum delay to compensate. A maximum delay was probably reasonable anyway because the neural network model require a lot of data training. Another aspect of a ReCWS is the warning strategy. Zardosht et al. (2013) proposed a decision making algorithm for accident situations based on V2V and advised drivers based on different scenarios. Tang and Yip (2010) found that warning strategies for collision avoidance are constrained by the length of events such as DSRC communication latency and detection rage.

Although studies have proposed several ReCWSs and algorithms recently, three challenges remain for DSRC-based ReCWS developments. Firstly, studies have yet to consider information transmission delays that exist in the process from data acquisition to warning decisions. Secondly, the impact of intrinsic system reliability/variability such as information delay and GPS error on safety distance should be considered. Finally, given the constraints of safety distances and driver reaction times, the system should offer the best warning and mitigation mechanisms for drivers.

The purpose of this paper is to improve the accuracy of DSRC-based rear-end warning system, and to calibrate and validate the parameters in DSRC-based systems in real life. In order to precisely compute the information transmission delay in the system, we map out the exact information transmission processes in the system and present them in an information transmission delay model. To analyze the impacts of GPS error and information transmission delays on safety distance, an error-component safety distance model is proposed based on a traditional kinematic model. In addition, the system contains a warning strategy that suggests one of three different levels of braking force depending on the scenario.

This paper contains seven sections. In Section 2 we set up the rear-end collision warning system infrastructure. Section 3 analyzes the information transmission process and proposes the delay model of the system. In Section 4 we present the proposed safety distance model based on V2V communication. Section 5 develops a warning strategy. In Section 6 we present experiment results. In Sections 7 conclusions are presented.

## 2. System architecture

The DSRC device based on the proposed IEEE 802.11p standard has a bandwidth in the 5.9 GHz range (IEEE Task Group p). V2V and V2I communication uses these DSRC devices. Based on the information received from other vehicles, the proposed warning system uses information from the DSRC BasicSafetyMessage (BSM) to compute whether there is any potential danger of collision. The BSM is the core data transmitted through V2V and V2I applications and includes information about the vehicle including its unique MAC address, its position (latitude, longitude, elevation and position accuracy), motion (speed, acceleration, direction, control brake) and size (Liu and Khattak, 2016). The system uses CAN-BUS (Controller Area Network Bus) to transmit data between the controller and the actuator on the vehicle and includes basic data from the vehicle speedometer. However, manufacturers normally encrypt the CAN data and different manufacturers use different encryption methods. It is difficult to get data directly from the CAN and other sensors have to be used to collect the data to encode as the BSM message. We describe how we gather relevant vehicle information in our proposed system blow.

Our DSRC-based ReCWS is developed with three units (shown in Fig. 1): the data acquisition module, the DSRC equipment, and the vehicle terminal (the control and display module). The data acquisition module is responsible for collecting information such as speed and acceleration. The module uses an on-board diagnostic (OBD) system integrated with the acceleration sensor to collect the acceleration and speed information. A moving average filter filters data from the sensors. The DSRC device, which has an integrated GNSS module, is responsible for collecting GPS information, along with broadcasting and receiving BSM messages. The vehicle terminal is responsible for collision alarm

when appropriate. We use the smartphone as the vehicle terminal and develop the rear-end collision warning application based on an Android system. The vehicle terminal transmits data with DSRC via USB and receives data from the OBD via Bluetooth.

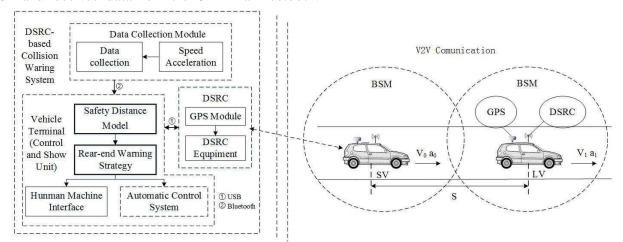


Fig. 1. Overall structure of the DSRC-based rear-end collision warning system

## 3. Analysis of system delays

Fig. 2 illustrates the information transmission processes in a ReCWS based on DSRC communication. The data acquisition module for the lead vehicle transmits information about the lead vehicle to the subject (following) vehicle via DSRC equipment. The vehicle terminal on the subject vehicle processes the information and sends any rear-end collision warning message to the on-board display unit. This transmission process contains three time delays: the lead vehicle's information collection, the information transmission from the front to the subject vehicle, and information processing once the subject vehicle has received.

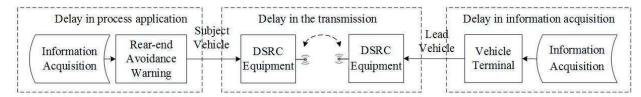


Fig. 2. The process of information transmission

It is important for warning systems to accurately account for these information delays. In the following discussions, we present how we modelled the three delay components and where we acquired the data sources in our proposed ReCWS.

(1) Delay in information acquisition

The information collection delay refers to the time it takes for the DSRC to generate information and send the information. The data collection unit collects speed and acceleration information at each cycle of T (ms) and transmits this information to the vehicle terminal. The terminal then integrates and encodes the information using multi-thread processing to form the BSM and sends the BSM at each cycle time  $T_d$  (ms). The collection cycle T is always less than the cycle  $T_d$ . Therefore, we take the delay  $T_c$  of information acquisition as

$$T_{c} = T_{d} - T \tag{1}$$

## (2) Delay in information transmission

The information transmission delay is the average travel time for data packets transmitted in the air media. DSRC radio is a single hop network, and its information transmission delay includes a network delay  $T_s$  (due to an accumulation of factors including backoff, busy channels, frame spacing, transmission delays and propagation delays) and an interface queuing delay  $T_w$  where messages wait to be sent (Ghadimi et al., 2011). We formulate the total information transmission delay  $T_w$  as:

$$T_{tr} = T_s + T_w \tag{2}$$

In our proposed ReCWS, we calibrated the delay parameters for information transmission using field experimental data, described in Section 6.

(3) Delay in the application

The rear-end collision warning application, installed on the subject vehicle terminal, sends and receives messages, handles information, establishes safety distance models and provides warning commands. The different computer programming codes developed to execute the calculations have different structures and functions, so they all have different computing times. The system computes the warning result after it updates all the required data. Assume that the program receives the broadcast message at time  $T_r$ , and generates the warning result at time  $T_e$ . The main information delay  $T_{ap}$  of the system is therefore

$$T_{ap} = T_e - T_r \tag{3}$$

where  $T_r$  and  $T_e$  is recorded by a time stamp during application, so that  $T_{ap}$  can be measured in the ReCWS.

Taking all three delay components described above, the overall information transmission delay of a ReCWS is

$$T_{d} = T_{c} + T_{tr} + T_{ap} \tag{4}$$

## 4. An error-component safety distance

Typically, there are two components to collision avoidance: safety distance and time to collision (TTC) (Bella et al., 2011; Ward et al., 2015). The safety distance algorithm calculates a safety distance based on vehicle kinematics (speed, acceleration) and delays in human response. Examples of safety distance algorithms include the National Highway Traffic Safety Administration (NHTSA) algorithm (Brunson et al., 2002), the CAMP algorithm (Kiefer et al., 2003) and the Mazda algorithm (Ararat et al. 2006). The TTC algorithm is used to measure the risk of collision. It is defined as the time until a collision between two vehicles would have occurred if the collision course and speed difference were maintained (Minderhoud and Bovy, 2001; Mohebbi et al, 2009). The two algorithms can be converted to each other. This paper uses the safety distance to determine the danger of collision. We propose an error compensation safety distance method (EC-SDM) based on vehicle kinematics.

A rear-end collision avoidance scenario occurs if the lead vehicle is either stationary or moves slower than the subject vehicle. We made the following assumptions during the development of our safety distance method: (a) the lead vehicle will maintain constant deceleration until it stops; (b) the subject vehicle will maintain its current speed and acceleration during a fixed reaction time and then decelerate at a prescribed level; and (c) when the system warns to brake, the braking deceleration of subject vehicle is always greater than or equal to that of the lead vehicle. As shown in Fig. 3, we use LV to mark the lead vehicle and SV to mark the subject vehicle. Assume that at initial time  $t_0$ , the distance gap between vehicles LV and SV is  $d_m$ . Let the initial speed and acceleration of the LV be notated as  $V_{10}$  and  $a_{10}$ , and let the initial speed and acceleration of the SV be  $V_{s0}$  and  $a_{s0}$ , where  $V_{10} < V_{s0}$ . The total safety distance can be divided into three parts. First, the distance  $d_i$  that the SV travels after it receives the warning and begins to decelerate. Second, the relative moving distance  $d_r$  when the SV uses desired deceleration  $a_s$  to slow down until the relative speed is zero. Third, the minimum headway distance  $d_r$  that the lead vehicle and the SV need to keep when the relative speed is zero. Therefore, we express the safety distance S for rear-end collision avoidance as:

$$\mathbf{S} = \mathbf{d}_{i} + \mathbf{d}_{r} + \mathbf{d}_{f} \tag{5}$$

where  $d_r = d_{es} - d_{el}$ ,  $d_{es}$  is the traveling distance for when the SV keeps deceleration  $a_{sd}$  until the speed is consistent with the lead vehicle.  $d_{el}$  is the distance that the LV travels over time  $T_{sr}$ . The headway distance is  $d_f = (L_s + L_1)/2 + d_0$ , where  $L_s$  and  $L_1$  denote the length of the two vehicles, and  $d_0$  is the final minimum distance kept between the two vehicles.

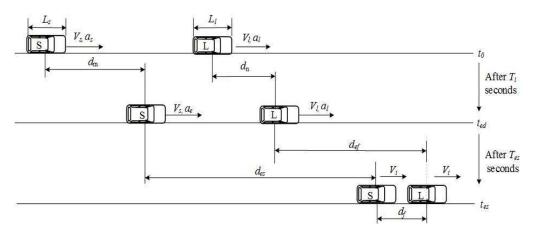


Fig. 3. Time series analysis of braking for rear-end collision avoidance

Time  $T_{sr}$  is the reaction time of the subject vehicle which is the time from when it receives the warning to when it activates braking (driver reaction time and mechanical brake delay). During time  $T_{sr}$ , the SV maintains its state of motion so

$$d_{i} = d_{s} - d_{l} = (v_{s} - v_{l}) * T_{sr} + \frac{1}{2} (a_{s} - a_{l}) * T_{sr}^{2}$$
(6)

In this system we calibrate driver reaction time  $T_{sr}$  using our field experimental data, which is described later in Section 6. The expression for the relative speed between the SV and the LV after  $T_{sr}$  is

$$\Delta \mathbf{v} = \mathbf{v}_{\mathrm{s}} - \mathbf{v}_{\mathrm{l}} + \left(\mathbf{a}_{\mathrm{s}} - \mathbf{a}_{\mathrm{l}}\right) * \mathbf{T}_{\mathrm{sr}} \tag{7}$$

Before the safety distance is calculated, it is necessary to assume the desired deceleration of SV. The desired deceleration  $a_{sd}$  of the SV relies on road pavement conditions and the vehicle's braking power. During calculation of the warning, the desired deceleration is an estimated value or a presupposition value. The vehicle executes the desired deceleration when the system gives the warning in order to avoid collision. Under our assumption, we expect the desired deceleration of the SV to be greater than or equal to  $a_1$ . The desired relative deceleration of the two vehicles is

$$\Delta a = a_{sd} - a_1 \tag{8}$$

The relative distance d<sub>r</sub> for two vehicles is

$$d_{r}(\Delta v, \Delta a) = d_{es} - d_{el} = \int_{0}^{\Delta v} (\Delta v - \Delta a * t) dt = \frac{\Delta v^{2}}{2\Delta a}$$
(9)

However, we cannot apply a kinematic model based on ideal conditions to actual conditions. Actual conditions present a wide variety of deviations such as GPS error and information delay  $T_d$ . The accumulation of these deviations will eventually lead to a large difference between the assumed headway distance  $d_f$  and the real headway distance  $d_{hd}$ , which we express as

$$\mathbf{d}_{\mathrm{hd}} = \mathbf{d}_{\mathrm{f}} + \mathbf{d}_{\mathrm{Td}} + \Delta \mathbf{E}_{\mathrm{g}} \tag{10}$$

where  $d_{Td}$  is the relative distance travelled during the transmission delay period. From testing done in Section 6, we found that  $T_d^2 < 0.002s$  and can be ignored. Therefore

$$\mathbf{d}_{\mathrm{Td}} \approx \Delta \mathbf{v} * \mathbf{T}_{\mathrm{d}} \tag{11}$$

In Eq. (10),  $\Delta E_g$  denotes the difference in GPS errors between the LV and the SV, where  $\Delta E_g = E_{gs} - E_{gl}$ . Many factors such as the ionospheric effect and the tropospheric effect influence GPS error  $E_g$ , so it is difficult to establish an accurate error model. Some rear-end collision avoidance systems use the Gaussian distribution to compensate the error of GPS (Yang et al., 2003; Xiang et al., 2014). Other model GPS errors based on experimental test results (e.g. Liu et al., 2009; Rife and Pervan, 2012). For simplicity, we use the Gaussian distribution to represent the distribution of  $E_g$ 

$$\mathbf{E}_{g} \sim \mathbf{N}\left(\mathbf{u}, \sigma^{2}\right) \tag{12}$$

where u is the mean, and  $\sigma$  is the standard deviation. The horizontal positioning accuracy of the GPS on the DSRC equipment is 2.5m at 2DRMS (Datasheet, 2017). DRMS (Distance Root Mean

Squared) represents the square root of the average of square errors, which is defined as:

$$2\text{DRMS} = 2\sqrt{\sigma_x^2 + \sigma_y^2} \tag{13}$$

We assume that the two-directional distribution has the same standard deviation, i.e.  $\sigma_x = \sigma_y = \sigma$ , we can get  $2\sqrt{2\sigma^2} = 2.5$ ,  $\sigma^2 = 0.79$  (GPS Technical Support Materials, 2003). The u equals zero and generally a GPS receiver will not have a constant position bias (Xiang et al., 2014). Thus, we obtain

$$\mathbf{E}_{g} \sim \mathbf{N}(0, 0.79) \tag{14}$$

Therefore

$$\Delta E_{g} \sim N(0, 1.58) \tag{15}$$

The  $\Delta E_{_g}$  can be obtained by the probability density function

$$f\left(\Delta E_{g}\right) = \frac{1}{\sqrt{3.16\pi}} \exp\left(-\frac{\Delta E_{g}^{2}}{3.16}\right)$$
(16)

Through analysis of these equations, we can finally get the safety distance based on error compensation (EC-SDM)

$$S = (v_{s} - v_{l}) * T_{sr} + \frac{1}{2} (a_{s} - a_{l}) * T_{sr}^{2} + \frac{\Delta v^{2}}{2\Delta a} + T_{d} * \Delta v + \Delta E_{g} + d_{f}$$
(17)

where  $\Delta v$  is the speed difference between the two vehicles after reaction time  $T_{sr}$  (in seconds),  $\Delta a$  is the acceleration difference,  $d_f$  is the required safety headway distance,  $T_d$  is the delay in information transmission, and  $\Delta E_g$  is the difference in GPS error.

## 5. Collision warning strategy

The ReCWS is a driving assistance system that warns drivers how hard to brake if needed. The system's output is deceleration. In practice, it is difficult for drivers to perform the exact desired deceleration manually. Therefore, our ReCWS gives warnings based on ranges rather than specific deceleration rates. The designed ReCWS can provide measurement on the speed of the SV and distance between the two vehicles. The system can also receive the speed and accelerate of LV from the DSRC. We can calculate the desired deceleration of the SV by using data collected by the system.

Combining (6), (7) and (17), we get:

$$a_{sd} = \frac{\Delta v^2}{2(S_m - d_i - \Delta E_g - d_f)} + a_1$$
(18)

where  $S_m$  is the measured relative distance between the two vehicles. Different decelerations can cause different driving experiences. We propose three warnings levels according to different conditions as illustrated in Table 1.

Table I Collision avo	idance warning strategy		
level of warning	Condition distance	Decelerated condition	braking
I Comfortable	$S(a_{c}) < S_{m} < S_{0}$	$a_{c} < a_{sd} < 0$	light
II Uncomfortable	$S(a_{mid}) < S_m < S(a_c)$	$a_{mid} < a_{sd} < a_{c}$	moderate
III Emergency	$S_m < S(a_{mid})$	$a_{sd} < a_{mid}$	hard

 Table 1 Collision avoidance warning strategy

In the table,  $a_c = -2m/s^2$  and  $a_{mid} = -5.5m/s^2$  are set for dry asphalt pavement given by Wu et al. (2009) and Brunson et al. (2002).

# 6. Field Test

In order to improve the accuracy and stability of the proposed DSRC-based ReCWS, we calibrated and tested the system repeatedly in a closed environment: Chang'an University's vehicle testing field. The testing field is a 2.4km high-speed circular runway, with a 1.1km straight section shown in Fig. 4. All experiments were performed on a single lane. We do not consider the influence of different lane vehicles in this paper, but lave-level location resolution can be solved by using the multi-sensor fusion positioning technology (Gu et al., 2016; Xu et al., 2018). Two vehicles were used (shown in Fig. 5): a BYD Automobile and a KIA-K3 Automobile, both with a length of 4.6m. The DSRC equipment used was the MK5 manufactured by Cohda Wireless. The Android application transmitted data with the DSRC via USB and received the data from the OBD via Bluetooth. The OBD module integrated the acceleration sensor and was able to read data from the interface. Fig. 6 displays the system setup. Table 2 shows the system parameter settings.



Fig. 4. Test site

Fig. 5. The test two vehicles



Fig. 6. The warning system

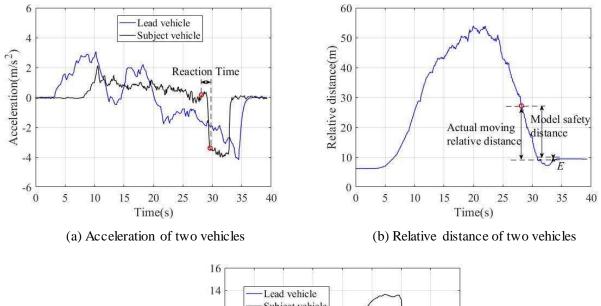
Table	2	Sy	stem	parameters	setting
-------	---	----	------	------------	---------

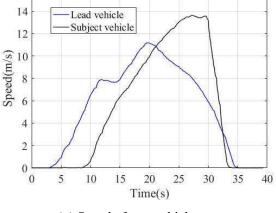
Model parameter	Setting value	
The cycle of the BSM sending $T_d$	50ms	
The cycle of the information acquisition T	40ms	
Delay in the information acquisition $T_c$	10ms	
Light brake $a_c$	$-2m/s^2$	
Moderate brake a <sub>mid</sub>	-5.5m/s <sup>2</sup>	
Minimum distance headway $d_{f}$	10m	
Final minimum space d <sub>0</sub>	5.4m	
Length of two vehicles $L_s = L_1$	4.6m	

## 6.1 Calibration and validation of safety distance models

In our proposed error compensation safety distance model (EC-SDM), key model parameters include the reaction time  $T_i$ , the delay in information transmission  $T_d$  and the GPS error  $\Delta E_g$ . The EC-SDM used to avoid collision is a little different from the car-following models (Colombaroni and Fusco, 2014), because of the assumption that the subject vehicle's braking deceleration is always greater than or equal to that of the lead vehicle. The proposed distance indicates the traveling relative distance of the vehicles in the whole collision avoidance process. Therefore, the data collection experiments were conducted in different independent collision avoidance scenarios. We calibrated and validated the EC-SDM following the procedure of Hollander and Liu (2008). The LV travels at

constant speeds or with different decelerations while the SV travels with different desirable decelerations according to the warning. The experiment software recorded the time of the warning, travelling states of both vehicles, and relative travelling distance. In order to calibrate the model, we collected 100 sets of data in two different scenarios: one where the lead vehicle is stationary and the other where lead vehicle is decelerating. Fig.7 shows one example case.





(c) Speed of two vehicles

Fig. 7. Exampled case: speed of lead vehicle is 40 km/h, while the speed of subject vehicle is 50 km/h, initial acceleration is  $0 \text{ m/s}^2$ , and desired deceleration is  $3.8 \text{ m/s}^2$ .

The mean difference between the model safety distance and the real measured relative distance quantifies the Measures of effectiveness (MOE). The model calibration adopts the following objective optimization model:

$$\min E \quad S.T. \left\{ \mathbf{P}_{\text{EC-SDM}} \in \mathbf{R}_{\text{EC-SDM}} \right\}$$
(19)

where  $E = \frac{1}{N} \sum_{i}^{N} |\hat{S}_{sim} - S_{real}|$ ,  $\hat{S}_{sim}$  denotes the simulated safety distance,  $S_{real}$  denotes the real

measured relative distance, P denotes the calibrated model parameters and R contains the parameter upper and lower bounds.

We used the Genetic Algorithm (GA) (Miettinen, 2012) to search for optimal parameters that enable the minimum MOE. The GA iteratively executes the EC-SDM and computes the MOEs at various parameter levels.

 $E_g$  is a series of discrete data which is measured and calibrated via a static measurement method. Let the lead vehicle remain static and the subject vehicle move gradually. We calibrate the GPS by comparing the distance measured by the GPS with the distance measured by a ruler. The  $\Delta E_g$  is obtained by the probability density function in formula (16).

The reaction time  $T_i$  is the time from when the SV first receives the warning to when it activates braking. The program recorded the warning times and the reaction times for each case as shown in the Fig.7. As a result, the  $T_i$  threshold boundary is

$$\mathbf{T}_{\mathbf{i}}^* \in \begin{bmatrix} 0.6\mathbf{s}, 1.6\mathbf{s} \end{bmatrix} \tag{20}$$

System delays have three parts. Field test results directly influence the calibration the delay in information transmission, while the system specifications directly affect the calculation of delays in information. In our experiment, two vehicles travelled a safe distance apart from each other using on-board DSRC devices to broadcast BSMs in single-hop mode. We recorded the time spent sending each a BSM packet (256 bytes) and the time spent receiving each packet at different driving speeds. Fig.8 displays the average and maximum transmission delays at different speeds. From the figure, the  $T_{tr}$  threshold boundary is

$$T_{tr}^{*} \in [0, 33 \text{ms}]$$
 (21)

The calibrated parameters are reaction time  $T_i$  and delay  $T_{tr}$ . Table 3 shows their value.

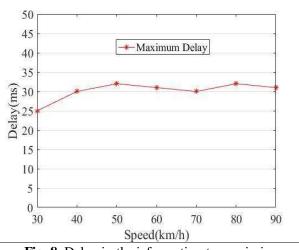


Fig. 8. Delay in the information transmission

Table 3 Calibrated parameters	
Model parameter	Optimal value
Delay in the information transmission(DIT) $T_{tr}$	19ms
Reaction time T <sub>i</sub>	0.85s

After obtaining the optimal system parameters, we tested the EC-SDM in further experiments to validate them. The lead vehicle travels at a constant speed or at different decelerations while the subject vehicle decelerates with different desirable decelerations according to the calibrated EC-SDM. We collected ten sets of data. The error between the simulated safety distance and the real relative travelling distance reflects the performance of the system. The data used in the evaluation applies separate measurements at each time-space point rather than at all measurements jointly. Therefore, the mean error (ME), and the mean percent error (MPE) help evaluate the system. These indicate systematic under or overproduction in the simulated measurements (Toledo and Koutsopoulos, 2012), and are given by

$$ME = \frac{1}{N} \sum_{n=1}^{N} \left( S_n^{sim} - S_n^{real} \right)$$
(22)

$$MPE = \frac{1}{N} \sum_{n=1}^{N} \frac{S_n^{sim} - S_n^{real}}{S_n^{real}}$$
(23)

where  $S_n^{sim}$  denotes the simulated safety distance and  $S_n^{real}$  denotes the real measured relative distance. ME =0.66 and MPE =0.084 are obtained in the validation. Theil's inequality coefficient

shows the relative error between the simulation value and the measured value (Toledo and Koutsopoulos, 2012), which is given by

$$U = \frac{\sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(S_n^{sim} - S_n^{real}\right)^2}}{\sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(S_n^{sim}\right)^2} + \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(S_n^{real}\right)^2}}$$
(24)

where U is bound,  $0 \le U \le 1$ . U = 0 implies a perfect fit between the simulation and measurement. U = 1 implies the worst fit. Table 4 shows the validation results.

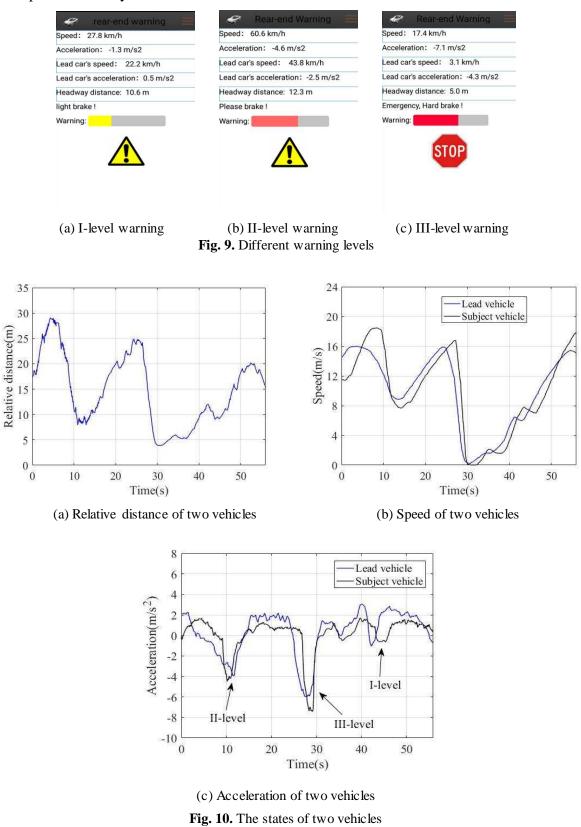
 Table 4 Safety distance model validation results

Scenarios				<b>C</b> ()	<b>G</b> ( )		105		
$a_{sd} (m/s^2)$	$v_{l}$ (m/s)	$a_1(m/s^2)$	$V_{s} (m/s)$	$a_s (m/s^2)$	S <sub>real</sub> (m)	S <sub>sim</sub> (m)	ME	MPE	U
-2	0	0	5.2	0.6	22.9	23.3			
-1.8	0	0	4.3	0	18.5	18.5			
-3.5	0	0	4.9	0.7	18.7	18.9		0.025	
-2	0	0	5.7	0.3	23.3	24.5	0.000		
-2.5	0	0	6.3	0.4	26.4	26.0			0.025
-5	7.2	-1.8	13.4	0.2	25.3	26.4	0.682	0.025	0.019
-6.5	5.1	-2.6	14.1	-0.4	34.1	34.0			
-6	6.3	-2.1	14.4	0	33.8	34.3			
-5.5	4.9	-2.8	12.2	-0.2	27.9	29.8			
-5.5	5.7	-1.5	15.2	-0.1	29.3	31.2			

#### 6.2 Test of rear-end collision warning system

The system proposes three levels of break warning strategy comfortable, uncomfortable and emergency. Different traveling states of the lead vehicle cause different influences on collision warnings. In this section, we present field experiments conducted under car-following scenarios to test the warning system. Fig. 9 shows the different warning interfaces displayed on smartphones. Fig. 10 shows the speed, acceleration and measured headway distance recorded by the experiment software.

The risk of collision will increase when the distance between the two vehicles is smaller than the safety distance. The warning level choice relies on the state of the lead vehicle and the gap between the two vehicles. Fig. 10 presents the deceleration profiles of both vehicles, where we can clearly see that the subject vehicle's speed decreases when the lead vehicle decelerates. The values of deceleration and spacing change more for warning level III than for level I. This analysis shows that the rear-end collision warning system has the ability to adjust the speed of the subject vehicle in order to improve its safety.



#### 6.3 Performance evaluation of the whole system

Performance evaluation focuses on the accuracy of the warning system. One performance

indicator is the timing of the warning signal. The system will not be effective if it gives the warning too late or too early. There is also one other metric used to evaluate performance: probability of correct warning P(c). We define this systematic error as the difference  $R_m$  between the measured spacing  $d_{fm}$  and the system-specified spacing  $d_0$  after the collision warning. When the systematic error belongs to  $\{R_m | R_m = |d_m - d_0| < T_n\}$ , where  $T_h$  is a threshold set to 2m, the warning is the correct warning.  $P(c)=(N_c / N)*100\%$ , where  $N_c$  is the number of correct warning and N is the total experiment times. To demonstrate the accuracy of the ReCWS, the proposed algorithm was compared with the safety distance model (SDM) and maximum compensation safety distance method (MC-SDM, Xiang et al., 2014). The SDM does not take communication delays and GPS error into consideration. The MC-SDM uses the maximum compensation for safety distance according to the GPS error. We have counted the correct warning rate of the system in different scenarios. Tables 5 and 6 show the fifteen test scenarios carried out as field test experiments on the straight road and ten test scenarios carried out on the slightly curvy road. Each scenario is tested 30 times for different safety model in each scenario. We recorded the spacing each time.

Table 5	Scenario	description	on the	straight line
Table 5	Decina 10	description	on the	strangin mit

Scenario (ID)	$V_1$ (km/h), $a_1$ (m/s <sup>2</sup> )	$V_{s} \text{ (km/h),}$ $a_{s} \text{ (m/s^{2})}$	Scenario (ID)	$V_1$ (km/h), $a_1$ (m/s <sup>2</sup> )	V <sub>s</sub> (km/h), a <sub>s</sub> (m/s <sup>2</sup> )
1	0, 0	20, 0	9	50, -1	50, 2
2	0, 0	30, 0	10	55, -1	60, 0
3	0, 0	40, 0	11	45, -5	50, 1
4	0, 0	50, 0	12	45, -5.5	60, 2
5	0, 0	60, 0	13	50, -6	40, 0
6	30, -1	50, 0	14	55, -5	60, 0
7	30, -1.5	50, 2	15	55, -5.5	60, 2
8	40, -2	55, 1			

Table 6	Table 6 Scenario description on the slightly curvy line						
Scenario	V <sub>1</sub> (km/h),	V <sub>s</sub> (km/h),	Scenario	$V_{l}$ (km/h),	V <sub>s</sub> (km/h),		
(ID)	$a_1 (m/s^2)$	$a_{s} (m/s^{2})$	(ID)	$a_1 (m/s^2)$	a <sub>s</sub> (m/s <sup>2</sup> )		
1	0, 0	30, 0	6	40, -1	45, 0		
2	0, 0	40, 0	7	45, -1.5	50, 0		
3	0, 0	45, 0	8	40, -4	50, 0		
4	0, 0	50, 0	9	40, -5	50, 1		
5	30, -1	40, 0	10	45, -5	50, 0		

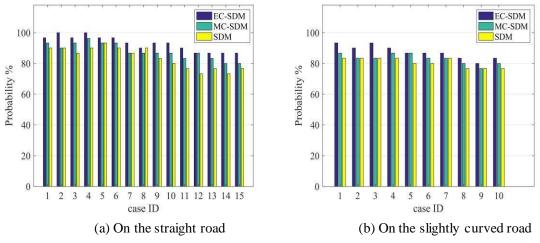


Fig. 11. The correct warning rates for different methods

The number of correct warning rates of ReCWS ranges from 100% to 86.7% on the straight road and 93.3% to 80% on the curved road, as shown in Fig.11. Note that a false warning does not mean an unsafe amount of space. On the contrary, a false warning is given when the error in spacing is too large. A vehicle has a risk of collision only when the error is negative. In the system experiment, there are no missing alarms, which may be due to our compensation for safety distance and the vehicle speed. We consider both the false warning and the missing warning rates as the incorrect warning rates of the system. The proposed algorithm improves the average of correct warning rates by 4.9% compared with the MC-SDM, and 9.12% compared to the SDM on the straight road. The system improves the average of correct warning rates by 4.3% compared with the MC-SDM, and 7.6% compared to the SDM on the slightly curved road. The correct warning rates has decreased compared with the warning rates on the straight road. The main reason is that the distance measured by GPS is smaller than the actual distance on the curve. The results of the correct warning rates suggest that our proposed warning system is reliable and effective.

# 7. Conclusion

This paper presents a DSRC-based rear-end collision warning system. We base the system on the explicit representation of functional and technical specifications of DSRC, including various system delay components. To compensate errors from GPS vehicle positioning, we developed an error compensation safety distance model. We also propose three collision warning strategies based on different levels of braking comfort.

Our field tests implemented the proposed warning system on a closed test track environment.

The results show that the proposed DSRC-based ReCWS can effectively provide correct collision warnings to the driver. Overall, the system achieves an average correct warning rate of 90% when the systematic error is 2m. The field tests also provided calibrated system parameter values, which will be useful for future studies and designs of DSRC-based ReCWS.

Although our proposed ReCWS has considered a number of parameters, we only measured it in testing scenarios and calibrated it using limited real vehicle experimental data. The accuracy of GPS is easily influenced by the driving environment, especially in cases of shielding. Multi-sensor fusion positioning technology is a promising method to improve the accuracy of safety distance calculation and to achieve lane-level location. We will integrate high precision positioning and collision warning system in the future. The parameter that we decided from the traffic environment could have been obtained by traffic flow statistics (Hollander Liu, 2008; Park and Schneeberger. 2006). Ongoing research needs to test this system in different kinds of traffic flows in order to validate it. Although our proposed ReCWS has considered many technical and system factors, such as delays in information transmission, GPS error and driver reaction time, some aspects of driver behavior and style such as age and skill (Abe and Richardson, 2004; Adell et al., 2011; Li et al., 2017; Toledo et al., 2007) are not included in this study. Cellular-V2X is the emerging technology which will be carried out in the future. Research shows the performance of C-V2X is more reliable than have been reported in IEEE 802.11p (Hu et al., 2017; Vukadinovic et al., 2018). An important direction for future research is to develop the C-V2X-based safety applications and tests in the real-life scenarios. In the future, we will analyze the influence of these behaviors on our ReCWS performance and do further experiments in complex real-life traffic environments with multi-vehicle communication.

## 8 Acknowledgments

This research was supported by the China National Science Foundation Grant No. 51278058, No. 61603058, No. 61703053, "111" Project on Information of Vehicle-Infrastructure Sensing and ITS No. B14043, Key research and development plan of Shaanxi Province No. 2018ZDCXL–GY04 -02, and the Fundamental Research Funds for the Central Universities No. 300102328108, 300102248301, and 300102249702. We also acknowledge the support from the National Natural Science Foundation of China (71890972/71890970), and the Royal Academy of Engineering Newton Fund project (UK-CIAPP/286).

## References

- Abdel-Aty, M., Hassan, H., Ahmed, M., Al-Ghamdi, A., 2012. Real-time prediction of visibility related crashes. Transp. Res. Part C: Emerg. Technol. 24, 288-298.
- Abe, G, Richardson, J., 2004. The effect of alarm timing on driver behaviour: an investigation of differences in driver trust and response to alarms according to alarm timing. Transport. Res. Part F: Traffic Psychol. Behav. 7, 307-322.
- Adell, E., Várhelyi, A., dalla Fontana, M., 2011. The effects of a driver assistance system for safe speed and safe distance-a real-life field study. Transport. Res. Part C: Emerg. Technol. 19 (1), 145-155.
- Alpar, O., Stojic, R., 2016. Collision warning using license plate segmentation. J. Intell. Trans. Syst., 20 (6), 1-13.
- Ararat, Ö. Kural, E., & Güvenç, B. A. (2006). Development of a collision warning system for adaptive cruise control vehicles using a comparison analysis of recent algorithms. In: Intelligent Vehicles Symposium, 2006 IEEE. IEEE, pp. 194-199.
- Bella, F., Russo, R., 2011. A collision warning system for rear-end collision: a driving simulator study. Procedia-Soc. Behav. Sci. 20, 676-686.
- Benedettoa, F., Calvi, A., Amico, F., Giuntaa, G, 2015. Applying telecommunications methodology to road safety for rear-end collision avoidance. Transport. Res. Part C: Emerg. Technol. 50, 150-159.
- Brunson, S.J., Kyle, E.M., Phamdo, N.C., Preziotti, G.R., 2002. Alert Algorithm Development Program: NHTSA Rear-end collision Alert Algorithm (No. HS-809526).
- Chen, C., Lv, N., Liu, L., Pei, Q., Li, X., 2013. Critical safe distance design to improve driving safety based on vehicle-to-vehicle communications. J. Cent. South Univ. 20(11), 3334-3344.
- Chiara Colombaroni & Gaetano Fusco, 2014. Artificial Neural Network Models for Car Following: Experimental Analysis and Calibration Issues, J. Intell. Transp. Syst., 18:(1), 5-16,
- Datasheet of Cohda Wireless MK5'GPS. Available: http://cohdawireless.com/Portals/0/MK5\_ OBU\_10122015.pdf. Last accessed on 2017.
- Dingus, T.A., McGehee, D.V., Mankkal, N., Jahns, S.K., Carney, C., Hankey, J.M., 1997. Human factors field evaluation of automotive headway maintenance/collision warning devices. Hum.

Factors 39, 216-229.

- Ghadimi, E., Khonsari, A., Diyanat, A., Farmani, M., Yazdani, N., 2011. An analytical model of delay in multi-hop wireless ad hoc networks. Wireless Netw. 17(7), 1679-1697.
- GPS Technical Support Materials of NovAtel Company. Accessible at <https://www. novatel. com/assets/Documents/Bulletins/apn029.pdf >. Last accessed on 2018.
- Gu Y., Hsu L.T., Kamijo S., 2016. GNSS/Onboard Inertial Sensor Integration with the Aid of 3-D Building Map for Lane-Level Vehicle Self-Localization in Urban Canyon. IEEE Transactions on Vehicular Technology, 65(6), 4274-4287.
- Hafeez, K.A., Zhao, L., Ma, B., Mark, J.W., 2013. Performance analysis and enhancement of the DSRC for VANET's safety applications. IEEE Trans. Veh. Technol. 62(2), 3069-3083.
- Hollander, Y., & Liu, R., 2008. The principles of calibrating traffic microsimulation models. Transport., 35(3), 347-362.
- Hu, J., Chen, S., Li, Z., Li, Y., Fang, J., & Li, B., Shi, Y., 2017. Link level performance comparison between LTE V2X and DSRC. J. Commun. Netw-s, 2(2), 101-112.
- Huang, C.M., Lin, S.Y., 2014. Cooperative vehicle collision warning system using the vector-based approach with dedicated short range communication data transmission. IET Intell. Transp. Syst. 8(2), 124-134.
- IEEE Task Group p, IEEE 802.11p-WAVE-Wireless Access for the Vehicular Environment Draft Standard.
- Jamson, A.H., Lai, F.C.H., Carsten, O.M.J., 2008. Potential benefits of an adaptive forward collision warning system. Transport. Res. Part C: Emerg. Technol. 16, 471-484.
- Khan, A.M., 2007. Intelligent infrastructure-based queue-end warning system for avoiding rear impacts. IET Intell. Transp. Syst. 1(2), 138-143.
- Kiefer, R.J., Cassar, M.T., Flannagan, C.A., LeBlanc, D.J., Palmer, M.D., Deering, R.K., Shulman, M.A., 2003. Forward Collision Warning Requirements Project: Refining the CAMP Crash Alert Timing Approach by Examining "Last-Second" Braking and Lane Change Maneuvers Under Various Kinematic Conditions. (Report No. DOT-HS-809-574).
- Li, G, Li, S., Cheng, B., Green, P., 2017. Estimation of driving style in naturalistic highway traffic using maneuver transition probabilities. Transport. Res. Part C: Emerg. Technol. 74, 113-125.

Li, L., Lu, G., Wang, Y., Tian, D., 2014. A rear-end collision avoidance system of connected vehicles.

In: Intelligent Transportation System (ITSC), 2014 17th international IEEE Conference on, IEEE, pp. 63-68.

- Liu, D., Bo, Y., and Zou, W., 2009. GPS error modeling based on time series and research on the accuracy of point positioning. Acta Armamentarii, 30(6), 825-828.
- Liu, J., Khattak, A.J., 2016. Delivering improved alerts, warnings, and control assistance using basic safety messages transmitted between connected vehicles. Transp. Res. Part C: Emerg. Technol. 62, 87-102.
- Miettinen, K., 2012. Nonlinear Multiobjective Optimization, vol. 12. Springer Science & Business Media.
- Minderhoud, M.M., Bovy, P.H.L., 2001. Extended time-to-collision measures for road traffic safety assessment. Accid. Anal. Prev. 33(1), 89-97.
- Mohebbi, R., Gray, R., Tan, H.Z., 2009. Driver reaction time to tactile and auditory rear-end collision warnings while talking on a cell phone. Human Fact.: J. Human Fact. Ergon. Soc. 51 (1), 102-110.
- Park, B., and J. D. Schneeberger., 2006. Microscopic simulation model calibration and validation. Transport. Res. Rec.: J. Transport. Res. Board. 1856(5), 185-192.
- Rasshofer, R.H., Spie, M., Spies, H., 2011. Influences of weather phenomena on automotive laser radar systems. Adv. Radio Sci. 9, 49-60.
- Rife, J. and Pervan, B., 2012. Overbounding revisited: Discrete-error distribution modeling for safety-critical GPS navigation. IEEE Trans. Aerosp. Electron. Syst. 48(2), 1537-1551.
- Tang, A., Yip, A., 2010. Collision avoidance timing analysis of DSRC-based vehicles. Accid. Anal. Prev. 42(1), 182-95.
- The U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA), 2015. Advancing Safety on American's Roads. Accessible at <a href="https://www.nhtsa.gov/equipment/safety-technologies">https://www.nhtsa.gov/equipment/safety-technologies</a>. Last accessed on 2017.
- Toledo T., Koutsopoulos H., 2012. Statistical Validation of Traffic Simulation Models. Transport. Res. Rec: J. Transport. Res. Board, 1876.142-150.
- Toledo, T., Koutsopoulos, H.N., Ben-Akiva, M., 2007. Integrated driving behavior modeling. Transport. Res. Part C Emerg. Technol. 15, 96-112.

Vukadinovic, V., Bakowski, K., Marsch P., Garcia I.D., Xu, H., Sybis, M., Sroka, P., Wesolowski, K.,

Lister, D., 2018. 3GPP C-V2X and IEEE 802.11p for Vehicle-to-Vehicle communications in highway platooning scenarios. Ad Hoc Networks, 74, 17-29.

- Wang, J., Wu, J., Li, Y., 2015. The driving safety field based on driver-vehicle-road interactions. IEEE Trans. Intell. Transp. Syst. 16 (4), 2203-2214.
- Wang, J., Wu, J., Zheng, X., Ni, D., Li K., 2016, Driving safety field theory modeling and its application in pre-collision warning system. Transport. Res. Part C: Emerg. Technol. 72, 306-324.
- Wang, Y., Wenjuan, E., Tian, D., Yu, G., Wang, Y., 2011. Vehicle collision warning system and collision detection algorithm based on vehicle infrastructure integration. In: Advanced Forum on Transportation of China (AFTC), 2011 7th international IET Conference on, IET, pp. 63-68.
- Ward, J. R., Agamennoni, G., Worrall, S., Bender, A., Nebot, E., 2015. Extending time to collision for probabilistic reasoning in general traffic scenarios. Transport. Res. Part C: Emerg. Technol. 51, 66–82.
- Wu, Z., Liu, Y., Pan, G. 2009. A smart car control model for brake comfort based on car following.IEEE Trans. Intell. Transp. Sys. 10(1), 42-46.
- Xiang, X., Qin, W., Xiang, B., 2014. Research on a DSRC-based rear-end collision warning model. IEEE Trans. Intell. Transp. Syst., 15(3), 1054-1065.
- Xu Q., Li X., Chan C.Y. 2018. Enhancing Localization Accuracy of MEMS-INS/GPS/In-Vehicle Sensors Integration during GPS Outages. IEEE Transactions on Instrumentation & Measurement, 99, 1-13.
- Yang L., Ji H. Y., Feron E., and Kulkarni V., 2003. Development of a performance-based approach for a rear-end collision warning and avoidance system for automobiles. Proc. Int. Conf. IEEE Intell. Veh. Symp., pp. 316–321.
- Yang, M.T., Zheng, J.Y., 2015. On-road collision warning based on multiple FOE segmentation using a dashboard camera. IEEE Trans. Veh. Technol. 64(11), 4974-4984.
- Zardosht, B., Beauchemin, S., Bauer, M.A., 2013. A decision making module for cooperative collision warning systems using Vehicular Ad-Hoc Networks. In: Intelligent Transportation System (ITSC), 2013 16th international IEEE Conference on, IEEE, pp.1743-1749.