Development of a Kinematic-Based Forward Collision Warning Algorithm Using an Advanced Driving Simulator

Xuesong Wang, Ming Chen, Meixin Zhu, and Paul Tremont

***Abstract*—An effective forward collision warning (FCW) system must be compatible with drivers' risk perceptions and behavioral responses. The Collision Avoidance Metrics Partnership (CAMP) developed a kinematic-based FCW algorithm to determine the minimum distance needed to stop safely under various levels of rear-end crash risk. The algorithm generates a linear function for predicting drivers' expected response decelerations (ERDs) by considering motions of the involved vehicles. This linear function works well when the risks perceived by drivers are low; however, at elevated risks when the lead vehicle (LV) decelerates at an unexpectedly high rate, or at high relative speeds, the warnings are triggered too late for the subject vehicle to avoid a rear-end collision. The current study extends the CAMP FCW algorithm to improve the handling of extreme high-collision-risk scenarios. A total of 111 brake-only noncollision events was presented in the Tongji University Driving Simulator, and drivers' braking behaviors were used to model their ERDs. We found that ERDs depended on the interaction of LV deceleration and relative speed. In response to this finding, a nonlinear function with an interaction term was combined with a linear function into a piecewise function that accommodated both higher and lower LV deceleration conditions. The applicable domain of the warning onset range was then computed for a wide range of kinematic conditions. Results showed the piecewise function to be a better predictor of ERD than the linear function, as well as to result in fewer driver rejections of the FCWs.**

***Index Terms*—Forward collision warning, driving simulator, kinematic-based algorithm, expected response deceleration, piecewise function.**

I. Introduction

REAR-END collisions continue to be a serious highway safety problem, accounting for almost 30% of all crashes in the US and in China [1], [2]. One approach to reducing rear-end crashes has been to develop Forward Collision Warning (FCW) systems. These in-vehicle systems monitor the roadway ahead of the host vehicle and warn the driver when a collision risk reaches a certain threshold. Extensive efforts have been devoted to the development of FCW systems, and findings to date confirm that FCW systems have the potential to reduce the number and severity of rear-end collisions [2], [4].

The core element of FCW systems is the warning algorithm. Existing warning algorithms can be classified as either perceptual-based or kinematic-based. Perceptual algorithms rely on empirical knowledge of risk indicator threshold values such as Time-to-Collision (TTC) to present warnings of an impending crash. These systems typically depend on range and speed data, and are therefore fairly easy to implement. In contrast, kinematic-based systems determine the warning based on a theoretical calculation of the minimum distance to stop safely. Kinematic-based systems require more detailed dynamic data including speed, range, relative deceleration rates, and drivers' reaction times, but are able to provide more accurate warnings.

The effectiveness of any warning, whether perceptual or kinematic based, is determined by its timing. Warnings presented too early will not be trusted by drivers, and warnings presented too late will not help prevent collisions [5]. Under the Collision Avoidance Metrics Partnership (CAMP) project, Kiefer *et al.* [3], [6] proposed a kinematic-based algorithm (referred to as the CAMP algorithm) to time the warning using the minimum safe distance for a Subject Vehicle (SV) to stop when behind a Lead Vehicle (LV). The CAMP algorithm used a linear function to predict drivers' Expected Response Decelerations (ERDs) based on the LV deceleration rate and relative LV and SV speeds. These ERD predictions were sufficiently accurate when deceleration rates were between 0 g and 0.39 g and SV speeds were between 30 and 60 mph. However, when the LV decelerated at an unexpectedly high rate or relative LV and SV speed differences were great, the linear ERD prediction function resulted in warnings incompatible with drivers' visual perceptions of the rear end collision risk. This occurred because the Warning Onset Range (WOR) decreased as the LV braked harder, leaving SV drivers insufficient time to respond—a condition inconsistent with drivers' risk perceptions as they expect more time to respond as the collision risk increases.

In this study, drivers' braking behavior under varying levels of rear-end collision risk were collected in the Tongji University Driving Simulator. The data were used to develop a kinematic-based FCW algorithm designed to improve the CAMP algorithm's response to high risk rear end crash situations. The new proposed algorithm was validated by checking the applicability domain of the WOR for a wide range of kinematic conditions.

Manuscript received July 6, 2014; revised June 25, 2015; accepted February 3, 2016. Date of publication April 14, 2016; date of current version August 25, 2016. This work was supported by the National Science Foundation of China under Grant 51522810. The Associate Editor for this paper was A. Eskandarian.

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Digital Object Identifier 10.1109/TITS.2016.2528508

II. Review of Previous FCW Algorithms

Forward Collision Warning (FCW) algorithms can be categorized into two main types: perceptual-based and kinematic-based. This section reviews these two types of FCW algorithms.

A. Perceptual-Based Warning Algorithms

Perceptual-based algorithms trigger warnings based on the time required for two vehicles to collide if they continue traveling at their current speed and path. When the *Time to Collision* (TTC) falls below the human perceptual threshold (as defined within the algorithm), a warning is activated to alert the driver.

According to Honda's TTC algorithm [11], when the human threshold value of the TTC falls below 2.2 sec, a warning is presented at the distance of R_{warning} (in meters):

$$R_{\text{warning}} = f(v_{\text{rel}}) = 2.2V_{\text{rel}} + 6.2 \tag{1}$$

where V_{rel} is the relative velocity (m/s) between two vehicles and 6.2 m is an additional safety margin.

A TTC algorithm developed by Hirst & Graham [4], used a 3.0 sec threshold value, but incorporated an additional speed adjustment to minimize nuisance warnings. The speed adjustment was set at 0.4905 m per km/h of the SV, and the warning was triggered at a distance calculated as:

$$R_{\text{warning}} = f(V_{\text{rel}}, V_{\text{SV}}) = 3V_{\text{rel}} + 0.4905V_{\text{SV}} \tag{2}$$

where V_{SV} is the velocity of SV. Later, Brown *et al.* [12] analyzed the Hirst & Graham algorithm using a micro simulation approach and changed the setting of the speed penalty to 0.9811 m per km/h (from 0.8339) to allow for a typical drivers' reaction time of 1.5 sec.

Bella & Russo [14] developed a perceptual-based algorithm based on drivers' car following behavior and evasive maneuvers, using data acquired in a driving simulator. Their algorithm uses the following equation:

$$R_{\text{warning}} = 1.25V_{\text{rel}} + 1.55V_{\text{SV}}. \tag{3}$$

It differs from the Hirst and Graham algorithm in that it has a shorter threshold TTC threshold value (1.25 sec) and a larger speed penalty value (1.55 sec).

Another perceptual-based algorithm, the inverse-TTC (i.e., $V_{\text{rel}}/\text{range}$) model [13] was developed by Kiefer *et al.* using data from the CAMP project [3], [6]. They examined 3536 last-second braking judgment trials and 790 last-second steering judgment trials under three different scenarios: *LV Stationary* (SV approaching a stationary LV), *Constant Delta V* (SV approaching a LV with constant relative speed) and *LV deceleration trials* (LV decelerating at a constant rate when SV is following LV). These trials were each conducted under normal and hard braking instructions. In the normal condition, drivers were told to apply brakes at the "last-second" that would still allow them to "normally" avoid the impending collision. Under the hard braking condition, drivers were told to apply brakes only at the last-second that would allow them to "just barely" avoid the impending collision. A best-fitting equation was generated for a dimensionless variable x, that was mapped onto the logistic function $p = 1/(1+e^{-x})$, with a range from 0 to 1. Given any value of an index x, that represents the necessary braking to avoid a collision, the corresponding probability p that the existing conditions are a hard braking onset scenario can be determined. By selecting a probability value of hard braking onset (referred as p^*), the timing of the warning can be identified as the point at which the observed p value exceeds the selected p^*. In the Kiefer *et al* study, the inverse TTC measure was the best predictor of whether or not a scenario was a normal or a hard braking condition. In this inverse-TTC model, three separate regression equations were developed for the three different scenarios of relative SV and LV movements.

If LV moving and braking:

$$x = -6.092 + 18.816\left(\frac{V_{\text{rel}}}{\text{range}}\right) + 0.0534(\text{SV speed in mph}).$$

If LV moving and not braking:

$$x = -6.092 + 12.584\left(\frac{V_{\text{rel}}}{\text{range}}\right) + 0.0534(\text{SV speed in mph}).$$

If LV stationary:

$$x = -9.073 + 24.225\left(\frac{V_{\text{rel}}}{\text{range}}\right) + 0.0534(\text{SV speed in mph}). \tag{4}$$

A potential strength of perceptual-based algorithms is they do not require real time knowledge of LV deceleration rates which can be difficult to collect. The inverse TTC algorithm developed by Keifer *et al.* [13] illustrates this as it can be implemented using only the knowledge of whether or not the LV is stationary, moving or braking. However, the simplicity of perceptual-based algorithms is offset by the disadvantage of requiring empirical knowledge of human perception to determine TTCs, and the fixed empirical perceptual threshold is sensitive to individual differences and driving environment variations.

B. Kinematic-Based Warning Algorithms

Consistent with perceptual-based algorithms that rely exclusively on range and speed data, kinematic-based algorithms also use deceleration rate and reaction time data to determine the minimum theoretical distance to stop safely. However, unlike perceptual algorithms that depend on empirical knowledge of human perception, kinematic-based algorithms determine the distance at which braking onset must occur if a collision is to be avoided.

Kinematic-based Stop Distance Algorithms (SDA) [15] present warnings when the range between the LV and SV is less than a Warning Onset Range (WOR) as determined by the following equation:

$$R_{\text{warning}} = V_{\text{SV}}RT + \frac{V_{\text{SV}}^2}{2a_{\text{SV}}} - \frac{V_{\text{LV}}^2}{2a_{\text{LV}}} \tag{5}$$

where R_{warning} is the WOR (m), V_{SV} is the velocity of SV (m/s), V_{LV} is the velocity of LV (m/s). The variables of RT (reaction time), a_{SV} (assumed deceleration of the SV) and a_{LV} (assumed deceleration of the LV), are defined as constants with values of 1.0 sec, 5.88 m/s^2 and 5.88 m/s^2 respectively. It should be noted that all the decelerations mentioned in this article are the absolute value of deceleration rate and no additional negative sign is needed.

An algorithm developed by Mazda [16] is similar to SDA algorithms, but adds a system delay and a minimum safety range. The WOR is given by

$$R_{\mathrm{warning}} = V_{\mathrm{SV}}\tau_1 + V_{\mathrm{rel}}\tau_2 + \frac{V_{\mathrm{SV}}^2}{2a_{\mathrm{SV}}} - \frac{V_{\mathrm{LV}}^2}{2a_{\mathrm{LV}}} + R_{\min} \quad (6)$$

where τ_1 is the system delay, τ_2 is the driver delay and $R_{\min}$ is the minimum safety range.

A modified version of Mazda's algorithm was developed by the California Partners for Advanced Transportation Technology (PATH) [17]. This algorithm uses a non-dimensional warning value, w to determine when to trigger the warnings or to automatically apply the brakes. The algorithm is defined as follows:

$$w = \frac{(R - R_{\mathrm{br}})}{(R_w - R_{\mathrm{br}})}$$

$$R_w = \frac{1}{2}\left(\frac{V_{\mathrm{SV}}^2}{a} - \frac{V_{\mathrm{LV}}^2}{a}\right) + V_{\mathrm{SV}}\tau + R_{\min}$$

$$R_{\mathrm{br}} = v_{\mathrm{rel}}(\tau_1 + \tau_2) + 0.5a_{\mathrm{LV}}(\tau_1 + \tau_2)^2 \quad (7)$$

where R is the actual vehicle range, R_{br} is the braking critical distance and R_w is the warning critical distance and τ is the sum of system delay and driver delay. When $0 < w < 1$, then $R_{\mathrm{br}} < R < R_w$, different modalities of warnings (visual or auditory) are triggered according to the value of w. When $w < 0$, then $R < R_{\mathrm{br}}$, the system applies the brakes automatically.

The SDA, Mazda and PATH algorithms all assume the deceleration rate of the SV and the LV are constant values. However, this assumption may lead to either early or late warnings in the real world because drivers' response decelerations vary under different scenarios. It is necessary therefore to consider both the SV and LV deceleration rates as variables if warnings are to be properly timed. Recall that Kiefer *et al.* [3], [6] developed a linear function of dynamic parameters to predict drivers' ERDs based on the CAMP's last-second braking database. They proposed the following ERD equation:

$$\mathrm{dec}_{\mathrm{SVR}} = 0.164 + 0.668(\mathrm{dec}_{\mathrm{LV}}) + 0.00368(V_{\mathrm{SV}} - V_{\mathrm{LV}}) - 0.078(\text{if LV moving}) \quad (8)$$

where $\mathrm{dec}_{\mathrm{SVR}}$ was the expected response deceleration rate (in g's) of SV, $\mathrm{dec}_{\mathrm{LV}}$ was the deceleration rate (in g's) of LV As the Kiefer *et al* study was conducted on a field track, they tested LV deceleration rates no greater than 0.39 g, and speeds no greater than 60 mph.

Fig. 1. Tongji University driving simulator.

To sum up, the kinematic-based approaches have shown the potential to deliver timely rear-end crash warnings. The CAMP algorithm is capable of considering the ERD as a variable using a linear predictive function, although this linear function may result in a potential problem at elevated risk scenarios. The current study will illustrate this problem and attempt to improve the CAMP algorithm by making it work for a wider range of risk scenarios.

III. Driving Simulator Experiment

Drivers' rear-end collision avoidance behavior was examined in the Tongji University driving simulator using a car-following task under scenarios differing in initial headway and LV decelerations.

A. Participants

Twenty-nine participants, 6 females and 23 males recruited from the population of licensed drivers in Shanghai served. Four showed symptoms of simulator sickness and were replaced with three others. All participants possessed a valid driver's license and had at least one year and 10,000 kilometers of driving experience.

B. Apparatus

The Tongji University driving simulator is shown in Fig. 1. This simulator, currently the most advanced in China, incorporates a fully instrumented Renault Megane III vehicle cab in a dome mounted on an 8 degree-of-freedom motion system with an X-Y range of 20 × 5 meters. An immersive 5 projector system provides a front image view of 250° × 40° at 1000 × 1050 resolution refreshed at 60 Hz. LCD monitors provide rear views at the central and side mirror positions. SCANeR studio software [18] presented the simulated roadway and controlled a force feedback system that acquired data from the steering

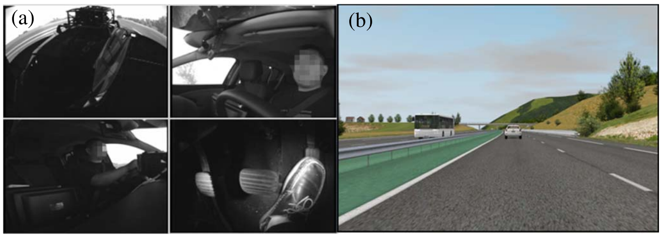

Fig. 2. (a) Video monitor analysis; (b) Experiment database.

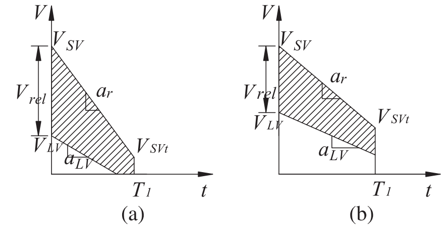

Fig. 3. Vehicle state parameters during a rear-end collision scenario. (a) LV stationary at colliding onset. (b) LV moving at colliding onset.

wheel, pedals and gear shift lever. The overall performance of this driving simulator was validated using three tests: simulator sickness, stop distance, and traffic sign size. Test results showed that the driving simulator satisfied the three criteria (i.e. at least 75% of participants show no simulator sickness, stop the car within 2 meters of the stop line and judge the realism of the traffic sign size) for validation.

C. *Experimental Design and Procedure*

A two-factor within-subjects design with three levels of LV deceleration (.3 g, .5 g, and .75 g) and two levels of initial headway (1.5 s and 2.5 s) was used to manipulate rear-end collision risk levels. The scenario presentation orders were balanced with preconditions. The 1.5 s/0.75 g rear-end scenario was arranged to never be the first of the 6 trials for any participant, and order effects of other scenarios were balanced using a pseudo-randomization procedure [19]. The purpose of using this design was to minimize stresses on the drivers that were observed during the pilot test where, after experiencing a high risk rear-end scenario (i.e. small initial time headway or large LV deceleration), drivers maintained a high alert state that affected their response and braking behaviors during subsequent scenarios.

Upon arrival at the driving simulator facility, participants were given an information summary and informed-consent document, and were asked to complete a questionnaire covering demographics, driving history, and several simulator sickness items. They were then briefed on simulator vehicle operation. Following these procedures, participants were asked to perform a normal car-following task in the simulator and to make any braking or steering maneuver necessary to avoid a collision. They were then given a 7-min practice drive during which they were told to follow a white LV at a distance between 60 m to 80 m on a straight road while the actual distance between their vehicle and the LV was displayed on a forward screen. This allowed participants to become familiar with simulated distances. Participants were visually monitored using four video cameras (please see Fig. 2 below).

Following the practice drive, participants were given a 5 minute break, and then asked to continue driving at about 120 km/h on the inner lane on a two-lane freeway under good weather daytime conditions with only light opposing traffic, (see Fig. 2(b)). After about 2 minutes, a white lead vehicle (LV) programmed to operate at a constant speed of 120 km/h moved in front of the SV. As in the practice drive, participants had been instructed to follow the LV at a distance between 60 m and 80 m. If the following distance exceeded 100 m, drivers received a "Speed Up" message to encourage them to follow the LV more closely. The LV was programmed to make 6 unpredictable full stops (with brake lights on) when headways were 1.5 sec or 2.5 sec at varying intervals that averaged 3 minutes. To make it difficult for the driver to anticipate the stops of the LV, its brake lights were turned on several times when it was not decelerating to a stop. When the LV was triggered to stop, the control program determined whether the driver was within the specified headway conditions of 1.5 s and 2.5 s. For headway conditions of 1.5 s, if the headway was outside the range, a "Speed Up" message would be displayed. Once the headway time reached 1.5 s, a 5 s period was used to check if the participants were following the LV steadily. Under the 2.5 s conditions, if the headway was outside the range, a "Speed Up" message would be displayed. If the headway time was between 1.5 s and 2.5 s, the control algorithm checked if the participants were following the LV steadily before triggering the LV stops. All the programmed events occurred on flat straight roads. Experimental sessions were completed after 6 full stops were made, and required about 20 minutes. A post-simulation survey of participants conducted showed that more than 60% of drivers said the vehicle dynamics, motion systems, and visual and audio systems of the driving simulator had a high level of realism.

D. *Measures of Deceleration*

Driving behavior data (e.g., throttle release and brake inputs) were recorded at a frequency of 20 Hz using SCANeR software. We focused on the deceleration rate necessary to avoid a collision and on the actual deceleration rate to predict drivers' ERDs. The required deceleration rate was calculated at SV deceleration onset (when the deceleration rate exceeded 0.1 g), and was defined as the minimum deceleration rate required for the SV driver to avoid a collision at SV deceleration onset [6]. Equation (9) incorporates an inequality to distinguish two moving states of LV when a collision could occur: stationary as in Fig. 3(a) and moving as in Fig. 3(b). The required deceleration rates for SV can be calculated with kinematic parameters.

$$a_r = \begin{cases} a_{\mathrm{LV}} + \frac{V_{\mathrm{rel}}^2}{2R}, & \text{when } R \leq \frac{V_{\mathrm{rel}} \cdot V_{\mathrm{LV}}}{2a_{\mathrm{LV}}} \\ \frac{V_{\mathrm{SV}}^2}{2\left(R + \frac{V_{\mathrm{LV}}^2}{2a_{\mathrm{LV}}}\right)}, & \text{when } R > \frac{V_{\mathrm{rel}} \cdot V_{\mathrm{LV}}}{2a_{\mathrm{LV}}} \end{cases} \tag{9}$$

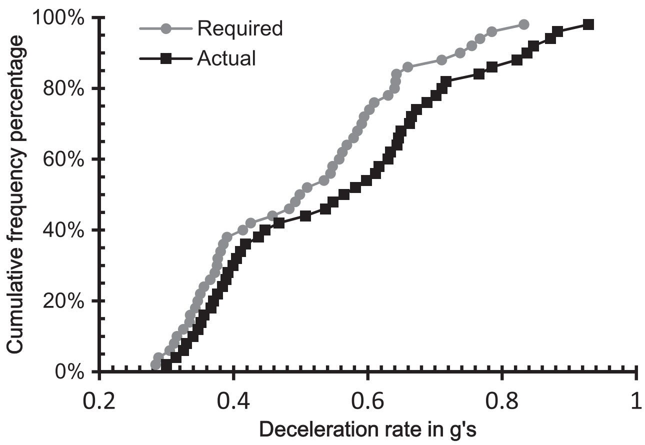

Fig. 4. Cumulative distribution of required and actual deceleration rates.

a_r is the rate at which SV must decelerate to avoid a collision, V_{rel} is the relative velocity between SV and LV, V_{SV} is the velocity of SV, a_{LV} is deceleration of LV, and R is the range between LV and SV at SV deceleration onset.

The driver's actual deceleration rate is the constant deceleration rate needed to yield the actual (observed) stopping distance, and was calculated for each braking event using the following equation:

$$a_{\mathrm{actual}} = \frac{V_{\mathrm{SV}}^2 - V_{\mathrm{SV}}'^2}{2\Delta S} \tag{10}$$

where V'_{SV} is the velocity of SV at the end of event, and ΔS is the distance travelled between SV braking onset and the end of the event.

IV. Development of the Kinematic-Based FCW Algorithm

A. *Distributions of Deceleration Measures*

Of the 174 rear-end scenarios simulated, drivers performed a brake only maneuver in 149, and a brake and steering maneuver in 25. For FCW development, only the 149 scenarios with brake-only maneuvers were of interest. Of these 149, 38 ended in collisions, and therefore the required and actual deceleration rates were calculated for the remaining 111. Recall the required deceleration rate is the constant deceleration rate necessary for the SV driver to avoid colliding with the LV vehicle, and is calculated from the point at which he initiates the deceleration. The actual deceleration rate is based on SV drivers' actual braking behavior during the whole crash avoidance procedure. Cumulative density distributions of required and actual deceleration rates are displayed below in Fig. 4.

Observe that the actual deceleration was greater than the required deceleration under all scenarios tested—a necessary outcome for events in which the SV does not collide with the LV. Observe also that the gap between required and actual deceleration rates becomes larger as the deceleration rate necessary to avoid a collision increases above 0.5 g. This finding suggests that drivers' can perceive the real collision risk more accurately at lower collisions risks than at higher collision risks.

TABLE I
Parameter Estimation of the CAMP Approach

Variables	Coefficients	*t*-statistics	*p*-value
dec_{LV}	0.75824	19.349	<0.001
$V_{SV} - V_{LV}$	0.0135	6.222	<0.001

B. *Prediction of Expected Response Deceleration*

The Expected Response Deceleration (ERD) predicts the rate at which drivers will decelerate by braking given a rear-end collision risk. The ERD should be compatible with drivers' natural braking behavior. If the ERD is much smaller than the driver's expectation, the FCW system will present a premature warning. But if the ERD is much greater than the driver's expectation, a late warning will be issued. In the CAMP project, Kiefer *et al.* [6] treated the ERD as a linear function of the LV deceleration rate and the relative speed of the LV and SV, leading to the use of linear regression to predict the ERD.

Based on the driving simulation experiment data from this study, a similar linear function for predicting ERDs following the CAMP approach can be developed. Table I presents the parameter estimation results of the linear function.

The equation below shows the linear function using CAMP approach.

$$\mathrm{dec}_{\mathrm{SVR}} = 0.0557 + 0.75824(\mathrm{dec}_{\mathrm{LV}}) + 0.0135(V_{\mathrm{SV}} - V_{\mathrm{LV}}) \tag{11}$$

where $\mathrm{dec}_{\mathrm{SVR}}$ is the predicted required deceleration to be considered as ERD (in g's), $\mathrm{dec}_{\mathrm{LV}}$ is LV's deceleration rate (in g's), V_S and V_{LV} were the velocities of LV and SV (m/s).

To check whether the ERD actually conforms to such a linear function, three typical scenarios were considered: (1) if the LV is decelerating at a rate of 0.7 g or greater while the relative speed is 15 m/s and relative range small, a driver would need a deceleration rate greater than 0.7 g to avoid a collision; (2) if the relative speed of LV and SV is around 0 m/s and the LV's deceleration rate remains at 0.7 g (to simulate a car-following with an unexpected LV stop scenario), the driver would need a deceleration rate greater than 0.7 g to avoid a collision; (3) if the relative speed is large enough (i.e., 30 m/s), drivers will tend to apply a hard brake regardless of the LV deceleration rate. From the three scenarios it can be seen that similar ERDs can be achieved given different relative speeds and different LV deceleration rates.

Based on the above, we may actually expect LV deceleration to interact with relative speed in the ERD prediction function because ERDs are supposed to be high when either LV deceleration or relative speed is high. Specifically, the effect of relative speed on the predicted ERD depends on the rate of LV deceleration. Similarly, the effect of LV deceleration also depends on the factor of relative speed. Fig. 5 presents a scatter plot of required deceleration rates versus relative speeds by LV deceleration to show this relationship based on our experiment data.

The result shows the extent of this interaction effect and can be readily observed as the trend lines would be parallel in the absence of an interaction effect. In this figure, the slope for LV's

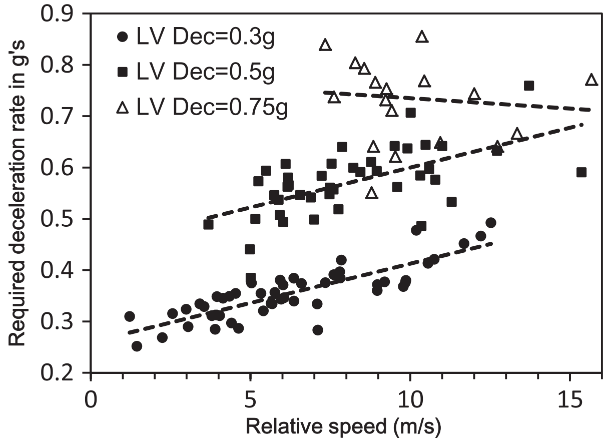

Fig. 5. Scatter plot of required deceleration rate versus relative speed by LV deceleration rate.

TABLE II
PARAMETER ESTIMATION OF THE NEW PROPOSED APPROACH

Variables	Coefficients	t-statistics	p-value
dec_{LV}	1.174	10.167	<0.001
$V_{SV} - V_{LV}$	0.033	5.955	<0.001
$(dec_{LV}) * (V_{SV} - V_{LV})$	-0.0472	-3.802	<0.001

deceleration when equal to 0.75 g is not parallel to the slopes of LV's deceleration rate when at 0.3 g and 0.5 g.

It follows that a linear function is not appropriate to capture drivers' natural response behavior because at high LV deceleration rates or at high relative speeds, linearity does not hold. An interaction term was therefore introduced into the model and the regression equation was revised to reflect the nonlinearity of the ERD function and the interaction term as follows:

$$\begin{aligned}\mathrm{dec}_{\mathrm{SVR}} = &-0.10996 + 1.174(\mathrm{dec}_{\mathrm{LV}}) + 0.033(V_{\mathrm{SV}} - V_{\mathrm{LV}}) \\ &- 0.0472(\mathrm{dec}_{\mathrm{LV}}) * (V_{\mathrm{SV}} - V_{\mathrm{LV}}). \quad (12)\end{aligned}$$

Table II shows the parameter estimation results of the new proposed approach.

The R squared values for the CAMP approach and this new approach are 0.82 and 0.86 respectively. In spite of the close R squared values, a comparison of counter plots presented in Fig. 6 below reveals the differences in their predictions. The CAMP approach is uniformly linear; however, the new proposed approach shows an arc-shaped pattern, predicting greater ERDs at either high LV deceleration rates or larger relative speed differences.

It should be noted that we did not compare the original CAMP predictive equation [3] to our findings because the CAMP findings were derived from field tests that limited the maximum LV deceleration rate to 0.39 g, whereas our driving simulator tests went as high as 0.75 gs.

Another key observation regarding this new proposed approach is that when both LV decelerations and relative speeds had low values (areas labeled in pink in Fig. 6(b)), the new proposed approach did not work as well as the CAMP approach: our predicted ERDs were relatively lower than those predicted

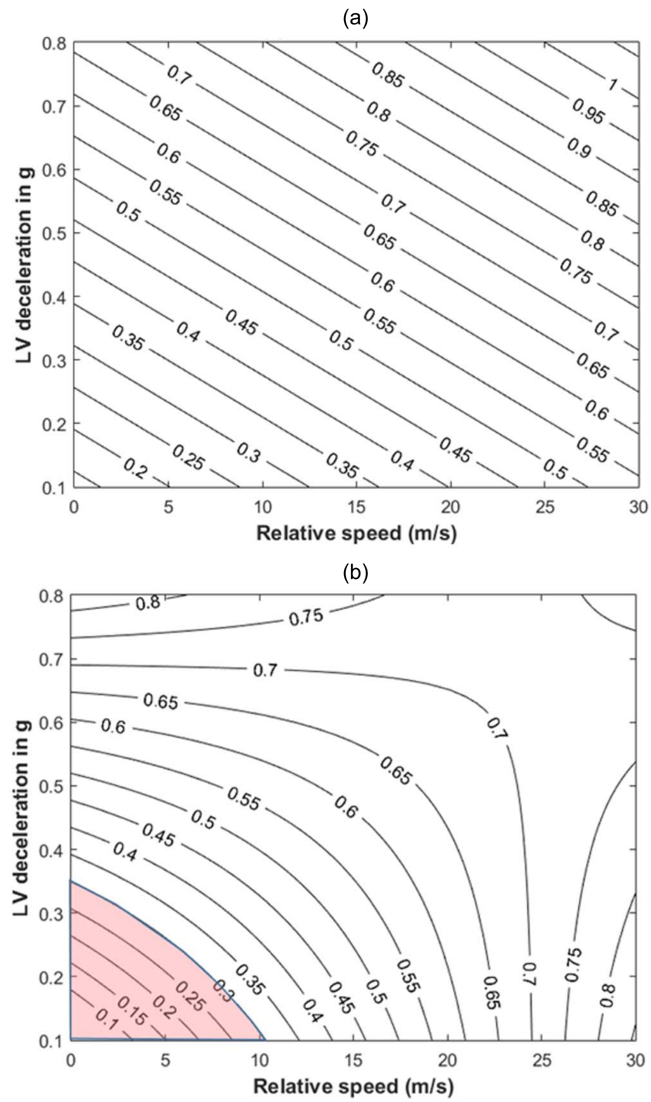

Fig. 6. Comparison of predicted response deceleration in g. (a) CAMP approach. (b) New proposed approach.

by the CAMP approach, and this could result in premature warnings because lower ERDs corresponded to longer warning onset ranges.

Given that the CAMP approach may be superior to the new proposed approach at lower decelerations, but not at higher decelerations, an approach that combines both the CAMP approach and the new proposed approach is needed. This was done by developing a piecewise function to combine the two prediction equations (Eq. (11) and Eq. (12)) to more accurately predict ERDs under low and high deceleration conditions. The final model for predicting drivers' ERDs is presented below

$$\begin{aligned}\mathrm{dec}_{\mathrm{SVR1}} &= 0.0557 + 0.75824(\mathrm{dec}_{\mathrm{LV}}) + 0.0135(V_{\mathrm{SV}} - V_{\mathrm{LV}}) \\ \mathrm{dec}_{\mathrm{SVR2}} &= -0.10996 + 1.174(\mathrm{dec}_{\mathrm{LV}}) + 0.033(V_{\mathrm{SV}} - V_{\mathrm{LV}}) \\ &\quad - 0.0472(\mathrm{dec}_{\mathrm{LV}}) * (V_{\mathrm{SV}} - V_{\mathrm{LV}}) \\ \mathrm{dec}_{\mathrm{SVR}} &= \begin{cases}\mathrm{dec}_{\mathrm{SVR1}}, & \text{if } \mathrm{dec}_{\mathrm{SVR2}} < 0.3 \text{ g} \\ \mathrm{dec}_{\mathrm{SVR2}}, & \text{if } \mathrm{dec}_{\mathrm{SVR2}} \geq 0.3 \text{ g}.\end{cases} \quad (13)\end{aligned}$$

C. Algorithm Logic for Computing the Warning Onset Range (WOR)

According to Kiefer *et al.* [3], the logic to compute the WOR can be summarized in four necessary steps.

Step 1: Calculate the total delay time from the onset of warning to SV deceleration. This total delay time is the sum of driver reaction time, plus 0.02 s to account for the typical delay between brake pedal application and actual deceleration of the vehicle. Drivers' reaction time to auditory warnings (default setting of standard FCW systems) was set at 1.3 sec which was at the 85th percentile based on the data collected in a separate brake reaction test. Then the projected speeds for SV and LV at SV deceleration onset are calculated as:

$$V_{\mathrm{SVP}} = V_{\mathrm{SV0}} - \mathrm{dec}_{\mathrm{SV0}} * \tau$$
$$V_{\mathrm{LVP}} = V_{\mathrm{LV0}} - \mathrm{dec}_{\mathrm{LV}} * \tau \tag{14}$$

where V_{SVP} and V_{LVP} are the projected speeds for SV and LV at SV deceleration onset respectively. V_{SV0}, V_{LV0}, $\mathrm{dec}_{\mathrm{SV0}}$, $\mathrm{dec}_{\mathrm{LV}}$ are initial (i.e. at LV deceleration onset) kinematic conditions, and τ is total delay time which equals to the sum of drivers' reaction time (1.3 sec) and vehicle system delay (0.02 sec).

Step 2: Calculate the ERD using Eq. (13).

Step 3: Compute the desired range at SV deceleration onset ("Brake Onset Range," BOR) and the decreased range during the total delay time ("Delay Time Range," DTR). The BOR should be computed for two possible situations: LV is stationary when SV and LV contact, (Case 1) and LV is moving when SV and LV contact (Case 2).

If $(V_{\mathrm{LV0}}/\mathrm{dec}_{\mathrm{LV}}) \le (V_{\mathrm{SVP}}/\mathrm{dec}_{\mathrm{SVR}}) + \tau$, where $\mathrm{dec}_{\mathrm{SVR}} > 0$, $\mathrm{dec}_{\mathrm{LV}} > 0$ (m/s^2), then LV is stationary when contacting (noted as "case 1");

Otherwise, LV is moving when contacting (noted as "case 2").

Then the BOR is calculated as following.

$$\mathrm{BOR} = \begin{cases} \frac{(V_{\mathrm{SVP}})^2}{2*\mathrm{dec}_{\mathrm{SVR}}} - \frac{(V_{\mathrm{LVP}})^2}{2*\mathrm{dec}_{\mathrm{LV}}}, & \text{case 1} \\ \frac{(V_{\mathrm{SVP}} - V_{\mathrm{LVP}})^2}{2*(\mathrm{dec}_{\mathrm{SVR}} - \mathrm{dec}_{\mathrm{LV}})}, & \text{case 2.} \end{cases} \tag{15}$$

And the DTR is calculated as following.

$$\mathrm{DTR} = (V_{\mathrm{SV0}} - V_{\mathrm{LV0}}) * \tau - 0.5 * (\mathrm{dec}_{\mathrm{SV0}} - \mathrm{dec}_{\mathrm{LV}}) * \tau^2. \tag{16}$$

Step 4: Compute the Warning Onset Range (WOR). The WOR is the sum of BOR and DTR.

$$R_{\mathrm{warning}} = \mathrm{BOR} + \mathrm{DTR}. \tag{17}$$

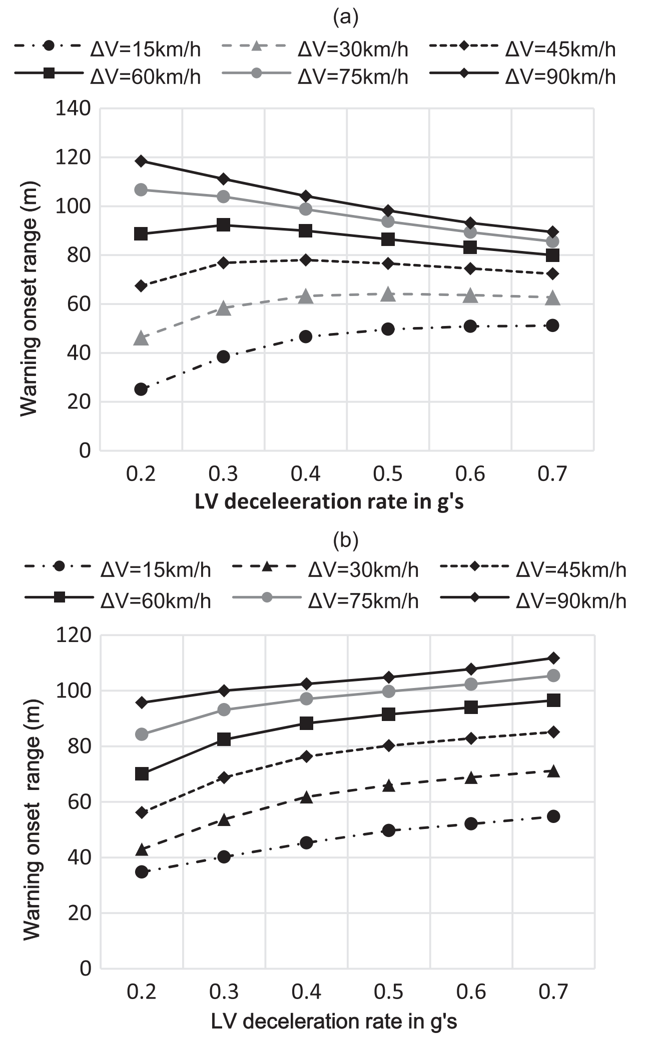

Fig. 7. Comparison of WOR for CAMP approach and new proposed approach. (a) CAMP approach. (b) New proposed approach. Note: The speed of SV is assumed as 120 km/h.

D. Validation of the New Proposed Algorithm

1) Incompatible Warning Range Issue: The differences between the CAMP approach and the new approach become evident when considering the WORs that result from adopting these approaches. Fig. 7 shows WORs of the CAMP approach decrease as the LV deceleration increases for the cases where relative speed is higher than or equal to 45 km/h. That is, the warnings are issued later when the LV brakes harder.

The problem is drivers expect more safety buffer time in higher risk scenarios while the CAMP approach provides shorter WORs, and this leaves drivers too little time to respond. The reason is that the predicted response deceleration increases linearly as the increase of LV deceleration and relative speed, and as these two parameters get larger (more dangerous), the calculated response deceleration rate becomes so large that it leads to shorter WORs. This problem will get worse as the LV deceleration and relative speed get higher. Such high risk scenarios are possible in the real world.

The new proposed approach fixes this problem by adopting a non-linear function with an interaction term to predict

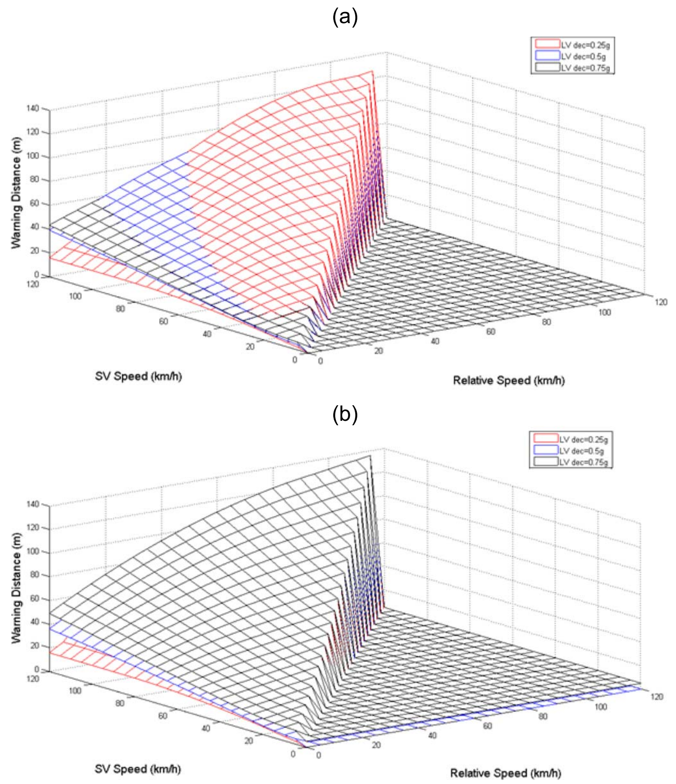

Fig. 8. Domain of Validity—(a) CAMP approach; (b) new proposed approach.

drivers' ERD. The remedy can be seen in Fig. 7(b). WOR systematically increases as the LV deceleration and relative velocities increase.

2) Domain of Validity: The domain of validity was calculated to check for obvious outliers or predictions incompatible with drivers' natural responses. Fig. 8 presents the domain of warning distance for both the CAMP approach (top) and the new proposed approach (bottom). The value of the LV deceleration rate is taken as 0.25 g, 0.5 g, and 0.75 g, and the SV speed and relative speed ranged from 0 to 120 km/h.

The domains presented show that the warning distance ranges from approximately 20 m to a maximum of 140 m for both the CAMP and the new proposed approach. Observe that the three surfaces appearing in the CAMP validity plot interweave, implying the warnings presented will be incompatible with drivers' expectations. Technically, only when relative speed is smaller than 20 km/h, is this not a problem. In contrast, the smooth surface of the new proposed approach implies that the algorithm can be effective under the tested conditions with no outliers. Furthermore, as the LV deceleration increases from 0.25 g to 0.75 g, the three surfaces rise systematically without any overlay areas appearing in the three-dimensional plot. This implies that the new proposed approach resolves the incompatibility issue, and makes for a more robust algorithm.

V. Summary and Discussion

In this study, drivers' braking behavior under different risk levels of rear-end scenarios were studied using the high fidelity Tongji University Driving Simulator. A total of 111 brake-only non-collision events were obtained from 29 drivers. These data were used to model drivers' crash avoidance behavior and to develop a kinematic-based FCW algorithm.

The current study tested car following scenarios where the LV deceleration rate reached up to 0.75 gs—a level that has been rarely examined in previous FCW studies. These high risk scenarios revealed that the required deceleration as perceived by the driver does not increase consistently as the LV deceleration and relative speed increase. When LV deceleration (or relative speed) is at a high level, the effect of relative speed (or LV deceleration) on the required deceleration is minor. To remedy this problem, this study proposed a non-linear function with an interaction term to predict drivers' ERD under high risk scenarios. The final ERD predictive function combines the linear and non-linear components that render it more consistent with drivers' natural braking behavior under both low and high risk scenarios.

The new ERD predictive function corrected the problem of the previous CAMP algorithm that led to warnings incompatible with drivers' perceptions—as the risk of scenario increases, the WOR gets shorter and results in too little time for drivers to initiate an avoidance maneuver. Consideration of the domain of validity under a wide range of kinematic conditions showed that the new proposed approach is adaptable to most real-world situations.

Driving simulators have been shown to be a reliable source of driver behavior data under rear-end collision scenarios [7], [8], and to be useful in the development FCW systems [9]. One common issue concerning driving simulators has been the validity of their results. The validity of the current study is supported by the following: 1) the Tongji University driving simulator passed an overall capabilities test on several dimensions that measured validity; 2) the maximum SV decelerations during rear-end scenarios ranged from 0.7 g to 1 g, which is consistent with previous studies (0.65–0.9 g) [19]; 3) subjective evaluations of realism obtained from participants indicated strong validity of the driving simulator.

Considering the FCW system application, the prediction accuracy of ERD relies on the obtainability of LV deceleration rates. Therefore, the robustness of new proposed algorithm to LV deceleration rates was investigated and showed a 5% error rate of LV deceleration estimates (with actual LV deceleration being 0.5 g) corresponded to less than 2% variations in the WORs. This suggests that the new proposed algorithm was not substantially affected by LV deceleration estimation errors.

Future research on the FCW algorithm proposed in this study will continue to test its effectiveness in preventing crash occurrence using the driving simulator, and will examine different rear-end crash scenarios with both audio and image warnings being provided to the drivers. The effects of the FCW system could then be evaluated based on crashes successfully avoided and other participant responses. Reiterating the main finding of this study, it is that a piecewise function is a better predictor of ERD than a linear function, and is more consistent with drivers' natural braking behavior, under both low and high risk scenarios and as such is a step toward the development of a reliable FCW system.

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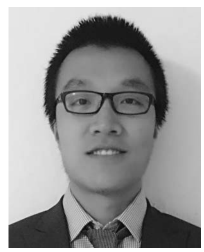

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