COLLISION AVOIDANCE SYSTEM WITH UNI-DIRECTIONAL COMMUNICATION FOR MITIGATING THE ADVERSE EFFECTS ON FOLLOWING VEHICLES

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ABSTRACT

Many types of advanced driver assistance system such as collision warning system and collision avoidance system are proposed to improve the vehicle's safety. The previous proposed systems contribute in reducing the occurrence of accidents and their severity. However, these systems produce a warning signal and activate the automatic braking based on the information of preceding vehicle using vehicle to vehicle communication, as well as information obtained by the sensors installed in the subject vehicle. These systems improve the safety of subject vehicle, but has a negative influence on the safety of following vehicles. Moreover, they disturb the subject vehicle's driving comfort by the extremely high deceleration rate. In this study, we propose a cooperative collision avoidance system that can predictively activate the automatic braking with uni-directional communication. This proposed system activates a minor deceleration in advance when a high collision risk is foreseen at the downstream. The proposed system is evaluated with a microscopic traffic simulation in various traffic scenarios with variation of traffic density, speed, vehicle class, and braking performance. The test results show that the proposed system effectively prevents the accident with relatively lower deceleration rate compared with the existing collision avoidance systems such as Mazda algorithm, Honda algorithm, and Berkeley algorithm. Due to the low deceleration rate, the occurrence of dangerous situations from other following vehicles is significantly reduced and the magnitude of shockwave is also attenuated.

Keywords: vehicle safety, cooperative, collision avoidance, shockwave attenuation.

1 INTRODUCTION

There have been numerous efforts to develop a variety of Collision Warning and Avoidance Systems (CWAS) in the field of Intelligent Transportation System (ITS). There are different types of CWASs according to directional characteristics such as longitudinal and lateral movements. The key of safety assurance in mitigating longitudinal collision risk is to provide the driver with either collision warning or avoidance service in appropriate time. To determine whether the CWAS is activated, there have been various types of safety surrogate measures for preventing hazardous events by characterizing different degrees of safety criticality. Earlier forward or rear-end CWAS, often had a time-based surrogate measure for mitigating the collision risk to the leader vehicle, such as Time-To-Collision (TTC) [1]. The CWAS using TTC considers the remaining time for two consecutive vehicles to collide based on the speeds and distances associated with the leader and following vehicles. However, the TTC and modified TTC algorithms cannot describe the expected time required for taking evasive action since they do not consider the response time at the beginning of deceleration when the following vehicle's driver recognizes a dangerous situation [2]. Moreover, the time-based CWASs does not consider the severity of the potential collision [3].

One frequently used safety surrogate measure in CWASs is distance-based measure. Unlike the time-based methods that only focus on issuing collision warnings to the drivers, the distance-based safety surrogate measure involves both warning and overriding criteria. It is based on different vehicle-to-vehicle kinematic situations, where the overriding indicates a function for the rear-end collision avoidance without human driver intervention, such as Automatic Emergency Braking System (AEBS). The main idea of the distance-based

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algorithm measuring the collision risk is to keep monitoring whether a hypothetical current braking distance D_c is less than either a critical warning distance D_w or a critical overriding distance D_o based on the current vehicle-to-vehicle kinematic condition [4]. The D_w and D_o are crucial criteria to determine if CWAS is required to operate at the current situation. They are determined based on various methodologies such as the models proposed by Mazda, Honda, and Berkeley(PATH). The previous studies on the distance-based models have proposed different approaches based on several hypothetical car-following scenarios. The Mazda algorithm takes into consideration a hypothetical car-following situation in which the leader vehicle starts to brake after a certain time delay. This results in a relatively longer D_o to mitigate the potential collision risk until the two consecutive vehicles come to a full stop [5]. The Honda algorithm considers two options; whether the leader vehicle comes to a stop before or after a specific stopping time of the leader vehicle, which often requires a much less D_o compared to the Mazda algorithm [6]. The Honda algorithm is designed to be a less conservative algorithm regarding the overriding function since it does not intend to avoid all possible collisions [7]. To prevent the overriding function from interfering with normal driving operations, the Berkeley algorithm involves a more conservative D_w to provide the driver with a wide range of cautionary warnings, and a non-conservative D_o to reduce the undesired effects of the overriding functions on the automatic brake interventions [8]. However, since these distance-based CWAS algorithms all assume that the deceleration rates of the leader and following vehicles are constant values [9], they still lack in consideration of the driver's braking characteristics on their safety surrogate measures such as accelerator release reaction time, accelerator-to-brake transition time, and brake-to-maximum brake transition time. To address the driving behaviour-related problems, Deceleration-based Safety Surrogate Measure (DSSM) that considers not only the transition time of individual driver but also the mechanical performance of each vehicle in high-risk situations of the collision was proposed [10]. The DSSM-based CWAS is capable of estimating the rear-end collision risk in both acceleration and deceleration phases compared to the other types of CWASs.

However, most of the existing CWAS algorithms have focused only on the impending rear-end collision risks associated with the change of the nearest leader vehicle movement detected by the on-board sensors without inter-vehicle communication [11]. The time delays due to the limited range and field of view sensors or braking behaviours may affect platooned vehicles approaching from upstream regarding mitigating the collision risks, particularly if they follow too closely when the leader vehicle activates the AEBS [12]. In other words, the disruptive downstream traffic conditions induced by activating the emergency braking may exhibit speed differences between the downstream and upstream traffics, which has negative effects on the upstream traffic safety and stability in terms of the collision risk and shockwave propagation [13], [14]. Nevertheless, there have been only few studies concerned with the negative effect of the AEBS on the traffic safety using inter-vehicle communication. The previous studies proposed a Model Predictive Control (MPC) based on the impact mitigation strategy to determine the desired deceleration rates for a group of vehicles in minimizing the potential severity of multi-vehicle collision using individual vehicular information obtained through the V2V communication. However, the proposed methodology is of doubtful validity in the context of achieving the stated objective in practice as some controversial issues can arise if it is implemented as "decentralized".

Since the collision risks of the upstream vehicles are highly influenced by the downstream traffic state, the downstream traffic information is helpful to proactively address the possible dangerous driving conditions in the subsequent seconds [15]. Based on the shared traffic information using the vehicle-to-vehicle communication, the vehicles approaching from the upstream section can reduce their speeds in advance when the downstream traffic state is unstable by traffic disturbances, which includes emergency braking or activation of AEBS. To further improve the reliability and validity of the present CWAS, this research analyzes the propagation patterns of collision risk to estimate the future collision risk of the subject vehicle by considering the collision risk of downstream area. Based on the analysis of propagation pattern of collision risk from downstream to upstream, this study aims to develop a Predictive Collision Risk-based CWAS (PCRC) to mitigate the negative impact of the existing CWAS on the traffic safety and stability. A comparison study is also conducted to evaluate the performance of the PCRC regarding the vehicle safety and traffic flow stability.

2 PREDICTIVE COLLISION RISK-BASED COLLISION AVOIDANCE SYSTEM

2.1 Modelling for collision risk propagation

To analyze the propagation pattern of collision risk in platooned vehicles, we estimate the collision risk of vehicles by using Deceleration-based Surrogate Safety Measure (DSSM) [10]. The DSSM shows more balanced accuracy in both acceleration phase and deceleration phase compared to other surrogate safety measures. The DSSM is expressed as a function of the maximum braking performance of a vehicle and required deceleration rate to avoid an accident as follows:

$$\begin{aligned} K= & [x_n(t)-x_{n-1}(t)+s_{n-1}]+[2\cdot v_n(t)+a_n(t)\cdot\tau]\cdot\frac{\tau}{2}- \\ & \left[v_{n-1}(t)/2+\frac{(a_{n-1}(t)+b_{max,\,n-1})}{4}\cdot\frac{(a_{n-1}(t)-b_{max,\,n-1})}{L_{n-1}}\right]\cdot\frac{(a_{n-1}(t)-b_{max,\,n-1})}{L_{n-1}}+ \\ & \left[v_n(t)/2+a_n(t)\cdot\tau+\frac{(a_n(t)+b_{max,\,n})}{4}\cdot\frac{(a_n(t)-b_{max,\,n})}{L_n}\right]\cdot\frac{(a_n(t)-b_{max,\,n})}{L_n} \end{aligned} \tag{1}$$

$$b_n(t)=b_{max,\,n-1}(t)\cdot\frac{[v_n(t)+a_n(t)\cdot\tau]^2}{\left[2\cdot K\cdot b_{max,\,n-1}(t)+v_{n-1}(t)^2\right]} \tag{2}$$

$$DSSM_{Sub,n}(t)=\frac{b_n(t)}{b_{max.n}}\ , \tag{3}$$

where a_n (t) is the acceleration rate of the following vehicle at time t, $a_{n-1}(t)$ is the acceleration rate of leader vehicle at time t, $b_{max.n-1}$ is the maximum braking rate of leader vehicle, which represents the vehicle's mechanical deceleration performance, $b_n(t)$ is the needed deceleration rate of the following vehicle to avoid the accident at time t, $b_{max.n}$ is the maximum braking rate of the following vehicle, $v_{n-1}(t)$ is the speed of leader vehicle at time t, $v_n(t)$ is the speed of the following vehicle at time t, L_{n-1} is the maximum variation of acceleration of leader vehicle, L_n is the maximum variation of acceleration of following vehicle, $v_n(t+\tau)$ is the expected speed of the following vehicle after τ, x_{n-1} (t) is the location of leader vehicle at time t, $x_n(t)$ is the location of the following vehicle at time t, τ is the perception-reaction time, and s_{n-1} is the length of leader vehicle.

The DSSM represents the collision risk with a ratio of a maximum braking performance of the subject vehicle to a required deceleration rate to avoid an accident when the leader vehicle abruptly reduces its speed with maximum braking performance. The DSSM value that is larger than one represents a more dangerous situation. Compared to the other surrogate safety measures, the DSSM additionally considers the transition time, which is the minimum time to change a state of the vehicle from acceleration state to deceleration state. The DSSM has three advantages to be used in the analysis of collision risk of platooned vehicles. Frist, the DSSM can analyze the collision risk pattern during not only deceleration phase but also acceleration phase. Second, the DSSM can well represent the personalized collision risk by utilizing each vehicle's mechanical performance. Third, the DSSM well captures the deceleration behaviour of the human driver when the driver is exposed to a high collision risk.

In the platooned vehicles, the collision risk propagates backwards, in other words, from downstream to upstream with a certain propagation rate. For example, in the situation of five platooned vehicles, the high collision risk of the first leader vehicle at time t propagates to other following vehicles with a different time interval (τ), which varies depending on the traffic state of each following vehicle. The collision risk of following vehicles at time ($\mathrm{t}+\tau$) highly depends on the collision risk of the first leader vehicle at time t. However, the collision risk of following vehicles may not only depend on the collision risk of the first leader vehicle at time t. The collision risk of following vehicles at time t can also affect the collision risk of following vehicles at time ($\mathrm{t}+\tau$).

To identify the variables that significantly affect the propagation of collision risk, a linear regression analysis is used. Regression analysis shows the relationship between dependent variable and explanatory variables and shows the statistical properties of the resulting estimators. Based on the statistical properties of the regression model, the explanatory power of independent variables can be identified. Furthermore, the regression analysis quantifies the relationship between collision risk of the following vehicle after a certain period and explanatory variables. The relationship can be used to improve the safety of platooned vehicles by controlling a dependent variable.

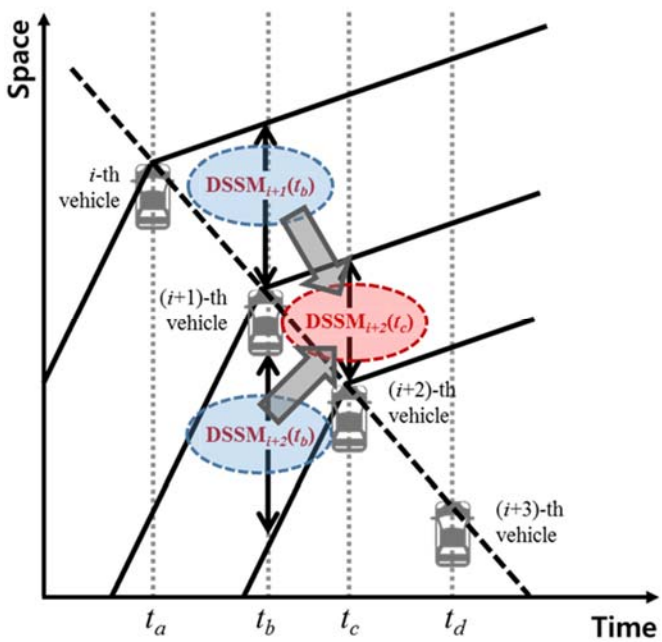

Figure 1: Variables for three regression models.

The regression model is analyzed for representing the propagation of collision risk. The variables for the regression model is graphically illustrated in Fig. 3 and the model is demonstrated by:

$$DSSM_{i+2}(t+\tau) = \alpha \cdot DSSM_{i+1}(t) + \beta \cdot DSSM_{i+2}(t), \tag{4}$$

where $DSSM_{i+1}(t)$ is the collision risk of preceding vehicle (i+1) of the following vehicle (i+2) at time t, $DSSM_{i+2}(t)$ is the collision risk of the following vehicle (i+2) at time t, $DSSM_{i+2}(t+\tau)$ is the collision risk of the following vehicle after time τ from time t. The regression model represents that the collision risk of the following vehicle at time $(\mathrm{t}+\tau)$ is explained by the combination of the collision risks of leader vehicle and the following vehicle at time t.

Fig. 2 shows the result of the regression analysis over the time interval τ. By evaluating the regression model with different time interval (τ), the changes in the accuracy of regression model over time interval τ is observed, and the effective time horizon of regression model to describe the propagation of collision risk is also identified. As shown in the Fig. 2, the R-squared value of the regression model is larger than 0.8 when the time interval τ is smaller than 4.1 seconds. This result represents that the collision risk of the following vehicle after time interval τ can be explained by the combination of collision risks of the leader and the following vehicles with higher explanatory power. The coefficient of $DSSM_{i+2}(t)$, which is the collision risk of the following vehicle at time t, is high when the time interval τ is small. As the time interval (τ) is increased, the coefficient of $DSSM_{i+2}(t)$ is decreased. On the other hand, the coefficient of $DSSM_{i+2}(t)$, which is the collision risk of the leader vehicle at time t, is increased from 0.09 to 0.58 when the time interval τ is smaller than 3.2 second. As the time interval τ is further increased, the coefficient of $DSSM_{i+2}(t)$ is decreased. Considering the trends of coefficients of these two dependent variables, when the time interval τ is near 1 second, the coefficient of the two dependent variables is 0.5. This result shows that the collision risk of the following vehicle after time interval 1 second is similarly affected by both dependent variables.

The results show that the future collision risk of the following vehicle after a certain period is highly influenced by both collision risk of the leader vehicle and the following vehicle at the current state. In this relation, the high collision risk of the leader vehicle is transferred to the following vehicle in the form of a weighted average of collision risk of the leader vehicle and that of the following vehicle. Especially, when the time interval is between 1 and 2 seconds, the collision risk of the leader vehicle and that of the following vehicle equivalently affects the future collision risk of the following vehicle. With this result, we design the cooperative DSSM ($DSSM_{co}$) to predict the future collision risk of the subject vehicle, and $DSSM_{co}$ is expressed as follows:

$$DSSM_{co,i}(t+\tau) = W_1 \cdot DSSM_{i-1}(t) + W_2 \cdot DSSM_{co,i-1}(t), \tag{5}$$

where $DSSM_{co,i}(t+\tau)$ is the cooperative DSSM of subject vehicle i at time $t+\tau$, $DSSM_{i-1}(t)$ is the DSSM of the preceding vehicle of the subject vehicle i at time t, $DSSM_{co,i-1}(t)$ is the cooperative DSSM of the preceding vehicle of subject vehicle i at time t, and W_1 and W_2 are the weight for calculation of the cooperative DSSM and these values are set to 0.5 in this study based on the results of regression analysis.

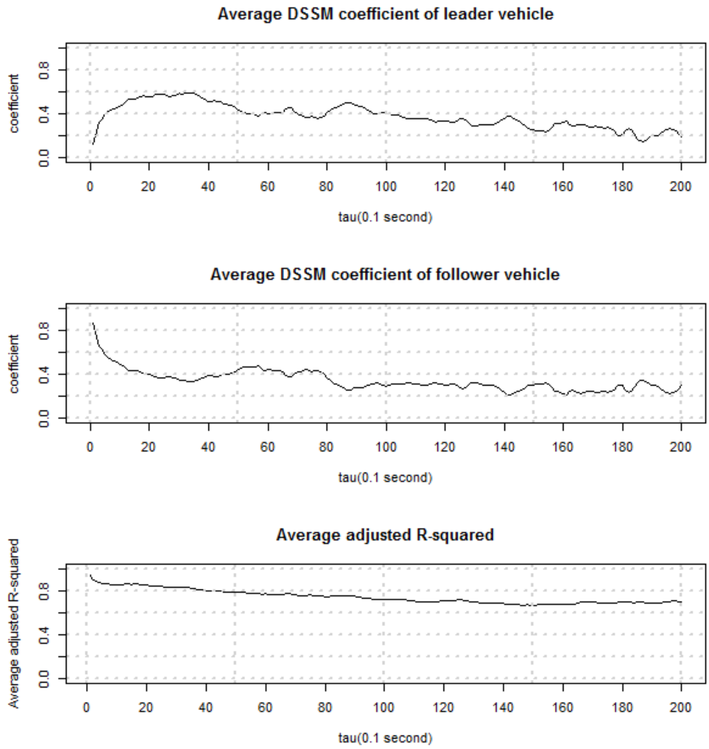

Figure 2: Results of regression model varying over time interval $\boldsymbol{\tau}$.

2.2 Predictive Collision Risk-based Collision avoidance system

With the DSSM of the subject vehicle and the cooperative DSSM of the subject vehicle, we propose a Predictive Collision Risk-based Collision avoidance (PCRC) system. Fig. 3 shows the control algorithm of the proposed PCRC system. In the previous researches, the DSSM value larger than 1.1 represented a dangerous situation, and the DSSM value larger than 1.3 represented a highly dangerous situation that had to be avoided [10], [15]–[17]. By referencing these values, we set the threshold value for collision warning and collision avoidance system. When $DSSM_{co}$ value is lower than $DSSM_{sub}$ value, the PCRC system makes the decision only based on $DSSM_{sub}$. In this situation, the PCRC system gives a warning signal to drivers when the calculated DSSM value is between 1.1 and 1.3 and activates the automatic braking with -7.8 m/s^2 deceleration rate for collision avoidance when the calculated DSSM value is larger than 1.3. On the other hand, when $DSSM_{co}$ value is higher than $DSSM_{sub}$ value, it represents that subject vehicle will experience a high-risk situation approaching from the downstream area, so the PCRC system controls the vehicle by considering the relationship between $DSSM_{co}$ and $DSSM_{sub}$. When $DSSM_{co}$ is higher than $DSSM_{sub}$ and $DSSM_{sub}$ is between 1.1 and 1.3, the PCRC system activates the automatic braking with moderate deceleration rate (-5m/s^2). Owing to this moderate braking action, the proposed PCRC system reduces the collision risk of the subject vehicle in advance when

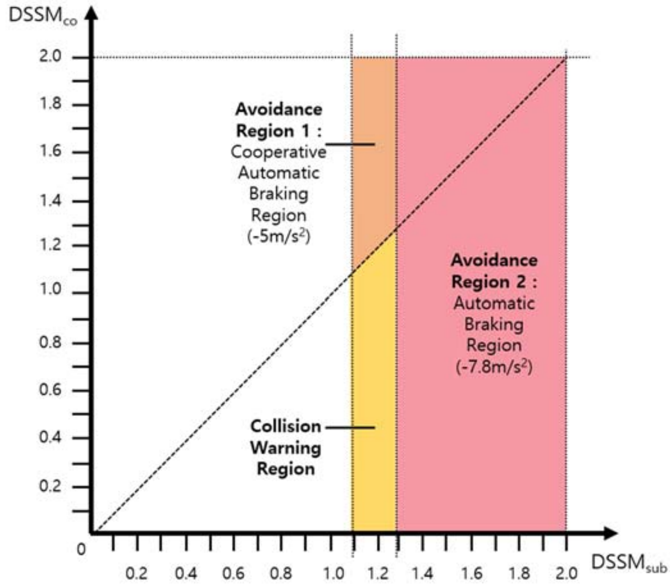

Figure 3: The control algorithm of PCRC system.

the high collision risk is arising from the downstream area. When $DSSM_{co}$ is higher than $DSSM_{sub}$ and $DSSM_{sub}$ is larger than 1.3, the PCRC system activates the automatic braking with -7.8 m/s^2 deceleration rate for collision avoidance.

The main difference of the proposed PCRC system compared to other collision avoidance system is that it reduces the speed in advance by estimating the future collision risk with $DSSM_{co}$. The situation where $DSSM_{sub}$ is moderate and $DSSM_{co}$ is high represents that the subject vehicle will be exposed to a highly dangerous situation even if $DSSM_{sub}$ is not significantly dangerous in a current situation. In this situation, the subject vehicle should reduce the speed with severe deceleration rate to avoid an accident. In some situations, this severe deceleration leads to multiple pile-ups because unstable traffic flow induced by sudden braking manoeuvre is one of the main causes of severe accidents. By preventing a severe deceleration with moderate pre-deceleration, the proposed PCRC system renders the traffic flow more stable than other collision avoidance systems. Therefore, the PCRC can improve a vehicle's safety, fuel efficiency, and driver's comfort.

3 COMPARISON ANALYSIS WITH SIMULATION MODEL

The performance of the proposed PCRC system is compared with the performance of the existing collision avoidance systems such as HONDA, MAZDA, and PATH in terms of frequency of severe deceleration and traffic flow stability. The following section details on comparison models and simulation.

3.1 Comparison models

There have been numerous CWAS models to be used to improve the vehicle safety. For the comparison analysis, this research considers the overriding functions with respect to three typical distance-based CWAS models, including Mazda, Honda and Berkeley.

The Mazda algorithm is one of the most conventional methods in the existing CWAS models. The Mazda algorithm assumes a hypothetical car-following scenario in which the leader vehicle starts to brake with deceleration rate -α_L after a certain time delay τ_2 when the consecutive vehicles maintain their constant speeds V_L and V_F respectively [5]. At the same time, the following vehicle starts to decelerate with –α_F after a reaction time delay τ_1 until the vehicles come to a complete stop. Based on the above scenario, the overriding distance D_O can be expressed as in Table 1. Unlike the Mazda algorithm, the overriding distance of the Honda algorithm is determined by comparing an expected stopping timing for the leader vehicle VL/αL with a system time delay τ2 [6]. It describes that the overriding distance DO is dependent on whether the leader vehicle would be able to stop within τ2, and is computed as the minimum safety buffer required to avoid rear-end collisions within τ2, as shown in Table 1. The Honda algorithm is designed to be a less conservative algorithm in terms of the overriding function since it does not intend to avoid all possible collisions [7]. In order to prevent the overriding function from interfering with normal driving operations, the Berkeley algorithm involves a non-conservative DO to reduce the undesired effects of the overriding functions on the automatic brake interventions [8]. It is assumed that the following vehicle starts to decelerate after a driver's reaction time τ at deceleration level -α when the leader vehicle applies the brake with a same deceleration rate. The corresponding DO is considered as the minimum safety buffer as shown in Table 1.

3.2 Simulation model

To evaluate the performance of the collision avoidance system in a dangerous situation, a car-following situation is simulated with Oversaturated Freeway Flow Algorithm (OFFA) [5]. The longitudinal movement of each vehicle is simulated by microscopic traffic variables such as location ($x_n(t)$), speed ($v_n(t)$) and driver related parameters such as reaction time (τ_n) and jam spacing (s_n^{jam}). Originally, the car-following model of OFFA is based on Newell's simplified car-following theory [6], however, this was modified in [7] to reduce computational loads in microscopic traffic simulation and avoid containing arbitrary parameters (known as short-gap mode).

The longitudinal movement is demonstrated as the following equation:

$$x_n(t+\Delta t) = \min\left(x_n^U(t+\Delta t), x_n^L(t+\Delta t)\right) \tag{6}$$

The upper boundary ($x_n^U(t+\Delta t)$) for updated location is:

$$x_n^U(t+\Delta t) = \min\begin{Bmatrix} x_{n-1}(t) - v_{n-1}(t)\cdot\tau_n - s_n^{jam}, \\ x_n(t) + v_n(t)\Delta t + a_n \Delta t^2, \\ x_n(t) + v_n^f \cdot \Delta t, \\ x_n(t) + \Delta x_n^s(t) \end{Bmatrix} \tag{7}$$

$$\Delta x_n^s(t) = \Delta t\left(b_n\tau_n + \sqrt{(b_n\tau_n)^2 - 2b_n\left(x_{n-1}(t) - x_n(t) - s_n^{jam} + d_{n-1}(t)\right)}\right) \tag{8}$$

$$d_{n-1}(t) = -\frac{\left(v_{n-1}(t)\right)^2}{2b_{n-1}}, \tag{9}$$

where $x_n(t)$ is position of vehicle n at time t, $v_n(t)$ is the speed of vehicle n at time t, τ_n is reaction time of vehicle n, s_n^{jam} is jam spacing of vehicle n, v_n^f is free flow speed of vehicle n, a_n is maximum acceleration rate of vehicle n, and b_n is maximum deceleration rate of vehicle n.

The lower boundary ($x_n^L(t+\Delta t)$) for the updated location is:

$$x_n^L(t+\Delta t) = \max\{x_n(t) + v_n(t)\Delta t + b_n \Delta t^2, x_n(t)\}. \tag{10}$$

Current car-following model is "accident-free" model, which cannot simulate a dangerous situation, this means that accidents do not occur in the simulation with the current car-following model. However, to evaluate the performance of collision avoidance system, dangerous situations should be demonstrated to actuate the collision avoidance system. In this study, to demonstrate unsafe situations and introduce accidents in the simulation, driver perception error is applied to microscopic traffic variables such as spacing and speed because most accident is occurred due to the perception error on the speed of leader vehicle, speed of the following vehicle, and spacing along with inattention on surrounding environment. The errors for position and speed ($\epsilon_x, \epsilon_{v,leader}$) of the leader vehicle are assumed to follow normal distribution with given standard deviation, which is proportional to spacing. The error for speed of the subject vehicle ($\epsilon_{v,subject}$) is assumed to follow normal distribution with given standard deviation. The equations reflecting errors are shown below:

$$x_{n-1} = x_{n-1} + \epsilon_x \tag{11}$$

where, $\epsilon_x \sim N(0, |x_{n-1} - x_n| \cdot \lambda_x)$

$$v_{n-1} = v_{n-1} + \epsilon_{v,leader} \tag{12}$$

where, $\epsilon_{v,leader} \sim N\left(0, |x_{n-1} - x_n| \cdot \lambda_{v,leader}\right)$

$$v_n = v_n + \epsilon_{v,subject} \tag{13}$$

where, $\epsilon_{v,subject} \sim N\left(0, \lambda_{v,subject}\right)$

Table 1: Overriding distance of each CWAS model.

CWAS model	Overriding distance
Mazda	$D_O = \frac{1}{2}\left(\frac{V_F^2}{a_F} - \frac{V_L^2}{a_L}\right) + V_F\tau_1 + \left(V_F - V_L\right)\tau_2 + D_{\min}$
Honda	$D_O = \begin{cases} (V_F - V_L)\tau_2 + \tau_1\tau_2 - \frac{a_1\tau_1^2}{2} & \frac{V_L}{a_L} \geq \tau_2 \\ V_F\tau_2 - \frac{a_1(\tau_2 - \tau_1)^2}{2} - \frac{V_L^2}{2} & \frac{V_L}{a_L} < \tau_2 \end{cases}$
Berkeley	$D_O = \frac{\alpha\tau^2}{2} + (V_F - V_L)\tau$

4 COMPARISON RESULTS

To evaluate the performance of collision avoidance system, we simulate 100 platoon cases, and each platoon case consists of ten following vehicles. The initial speed, spacing, preferred speed, and jam spacing are randomly generated to cover the various car-following situations. In all platoon cases, first vehicle reduces the speed with its maximum deceleration rate in the middle of the trajectory. Owing to this severe deceleration action, the following vehicles experience a highly dangerous situation. When the collision avoidance system equipped vehicle encounters this situation, they frequently reduce the speed with its maximum deceleration rate. This severe deceleration renders the traffic flow unstable and has a negative influence on the vehicle's safety. To identify this negative influence, we evaluate the performance of collision avoidance with a probability of severe deceleration action.

Fig. 4 and Fig. 5 show the probability of severe deceleration actions of different collision avoidance systems. As shown in Fig. 4, the proposed PCRC system reduce approximately 50% of the average occurrence of severe deceleration actions compared to other collision avoidance systems. This means that the proposed PCRC has a less negative influence on the following vehicles than other collision avoidance systems.

Fig 5 shows how the occurrence pattern of severe deceleration is changed according to the vehicle order. As shown in Fig. 5, the proposed PCRC system shows the lowest probability of severe deceleration in all vehicle order and most rapidly suppress the occurrence of severe deceleration. This result means that the proposed PCRC system would be more effective when the market penetration rate is high.

Fig. 6 shows the median value of vehicle speed before the vehicle meets the stopped vehicle and it shows how the proposed PCRC system can reduce the occurrence of severe deceleration action. The first vehicle reduces the speed with its maximum deceleration rate that is approximatively 30 seconds. As shown in Fig. 6, the proposed PCRC system reduce the speed in advance when the highly dangerous situation is expected, and the unsafe traffic

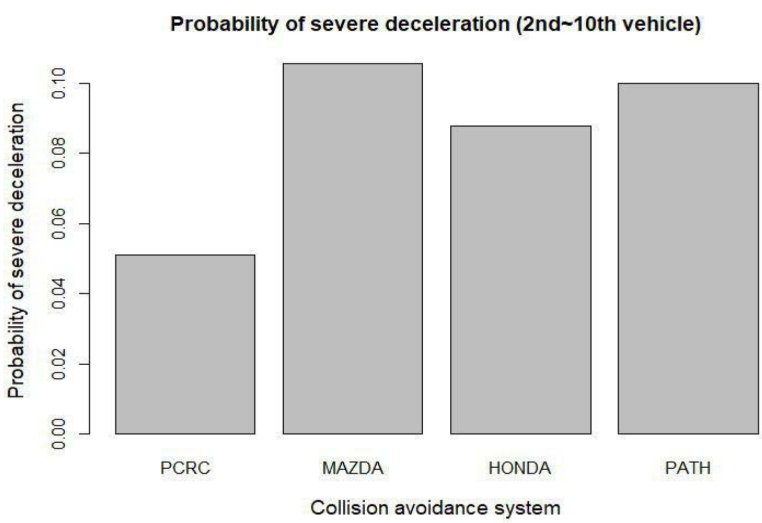

Figure 4: Average probability of severe deceleration from 2nd following vehicle to 10th following vehicle.

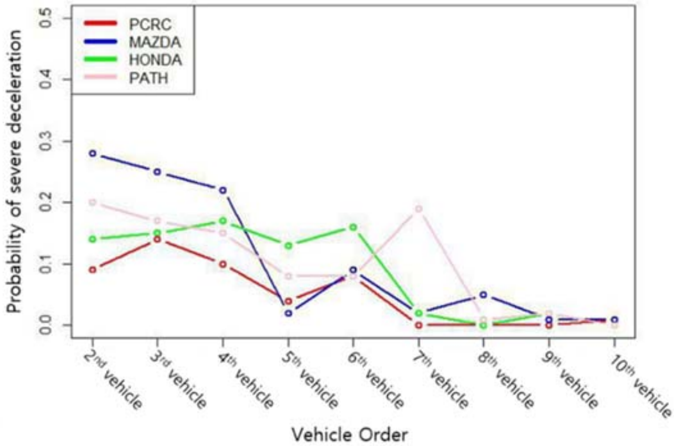

Figure 5: Probability of severe deceleration according to vehicle order.

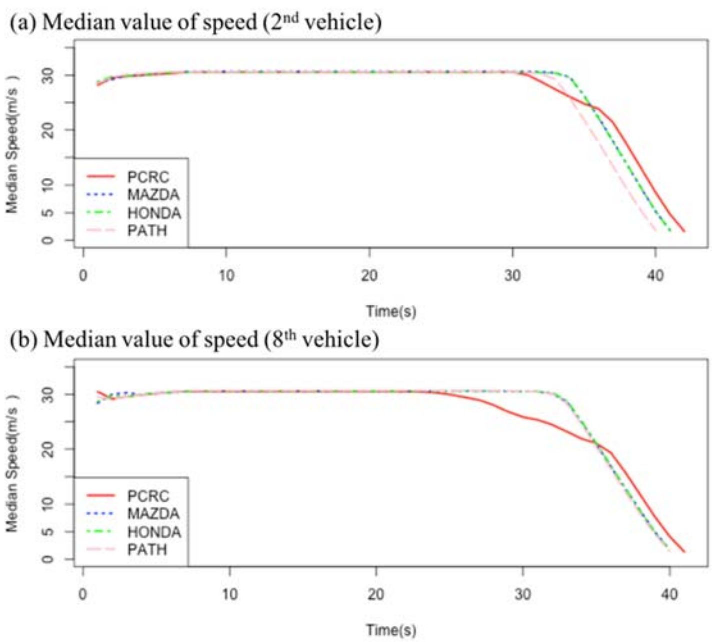

Figure 6: Median speed profile of collision avoidance. (a) 2nd vehicle; (b) 8th vehicle.

situation is detected by $DSSM_{co}$. Owing to the pre-deceleration with a moderate rate of the proposed PCRC system, the proposed system can prevent severe deceleration actions. Other collision avoidance system such as MAZDA, HONDA, and PATH reduce the speed with the maximum deceleration rate when they meet the stopped vehicle in all vehicle order. However, in the proposed PCRC system, a severe deceleration action occurs approximately 3~5 seconds later. Furthermore, the severity of shockwave caused by the first stopped vehicle is also reduced due to the pre-deceleration action of the proposed PCRC system.

5 CONCLUSION

In this paper, we propose the PCRC system based on the analysis of propagation pattern of collision risk. Moreover, the performance of collision avoidance systems are evaluated with a microscopic traffic simulation. As shown in the results, the proposed PCRC system can reduce the occurrence of severe deceleration actions of collision avoidance system because this it allows advanced speed reduction with moderate deceleration rate. Due to this feature, the proposed system would improve vehicle's safety and suppress negative influences on the collision avoidance system of traffic flow stability compared to other collision avoidance systems such as HONDA, MAZDA, and PATH.

In this study, we evaluate the performance of various collision avoidance systems in several scenarios by using traffic simulation. However, for practical application of the proposed system, we need to test the proposed system in various scenarios. It is suggested to evaluate the proposed system in field under different weather conditions and vary parameters such as truck vehicle ratio.

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