Connected Vehicle Technology Affected Safety Surrogate Measurement

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ABSTRACT

The Connected Vehicle (CV) safety systems improve the safety performance of a highway facility via assisting drivers in (re)acting properly under risky traffic conditions. This paper discloses and quantifies the cause-and-effect mechanism between such a behavior impact of CV and the traffic safety. A synthetic approach has been adopted to integrate the CV-affected behavior parameters into state-of-the-art traffic flow models. Resulting models are used to reproduce vehicle trajectories under the CV environment. Such trajectory data serve as the basis for computing the surrogate safety measurement, and thus describe the systematic safety performance of a highway facility. The effectiveness of the CV is examined in a case study for a freeway site in the greater Cincinnati area, Ohio. The study results find that the CV-affected perception-reaction time, desired headway and desired speed are responsible for the reduction of the traffic conflict frequency and decrease of the conflict intensity. The quantitative contribution of these behavior parameters has also been determined based on statistical analysis. The findings pave the technical foundation for successful deployment of the CV safety technologies into existing highway transportation systems.

Key Words: Driving behaviors; intelligent driver model; traffic conflicts; time-to-collision.

1. Introduction

The goal of this research is to systematically quantify the traffic safety improvement through the behavior adaptation of individual CV-equipped drivers. Results of the quantitative analysis are expected to enable the disclosure of the cause-and-effect mechanism between the CV-affected behaviors and the safety performance of the concerned highway facility. To achieve this goal, the research applies a synthetic approach that integrates the CV-affected driving behavior parameters into state-of-the-art traffic flow models. The functional relationships between the CV parameters (e.g., CV function type, message type, message timing and drivers' compliance level to CV messages) and drivers' behavior parameters (e.g., perception-reaction time, desired speed and desired following distance) are developed. The CV-affected behavior parameters are embedded into the microscopic traffic flow models as the factors that represent drivers' response sensitivity to traffic stimuli, such as relative speed and spacing between the subject vehicle and the leading vehicle [1]. The traffic flow models are further adopted to simulate the traffic operation of the concerned highway facility. Vehicle activity data obtained from the analysis provides a basis for computing the traffic safety measures that capture the safety performance of the facility.

The safety performance of a simulated highway facility is usually depicted by measures of effectiveness (MOEs) associated with traffic conflicts (near-miss traffic accidents), because the traffic conflicts are the most detailed safety-related events that the microscopic traffic flow models are able to realistically reproduce [2]. The traffic conflict is defined as "an observational situation in which two or more road users approach each other in space and time to such an extent that a collision is imminent if their movements remain unchanged" [3]. In analysis of traffic conflicting impacts, the surrogate safety measures are capable of depicting the frequency and intensity of the conflicts, and the likelihood that a conflict develops into a collision [4]. In this research, the frequency of the traffic conflicts is measured by the hourly number of conflicts [5]. The intensity of the conflicts is reflected by surrogate measures that depict the average duration of conflicts, the average risk level of conflicts, and the average kinematic energy exchanged in conflicts [6].

2. Methodology

The presented CV safety effectiveness modeling assumes that the drivers' behaviors are influenced only when the CV systems are interacting with them (i.e., when the CV systems are sending warning or advisory messages). Otherwise, the drivers will behave similarly to the non-CV equipped drivers. The methodology framework for identifying the safety impact of CV, is illustrated in **Fig. 1**.

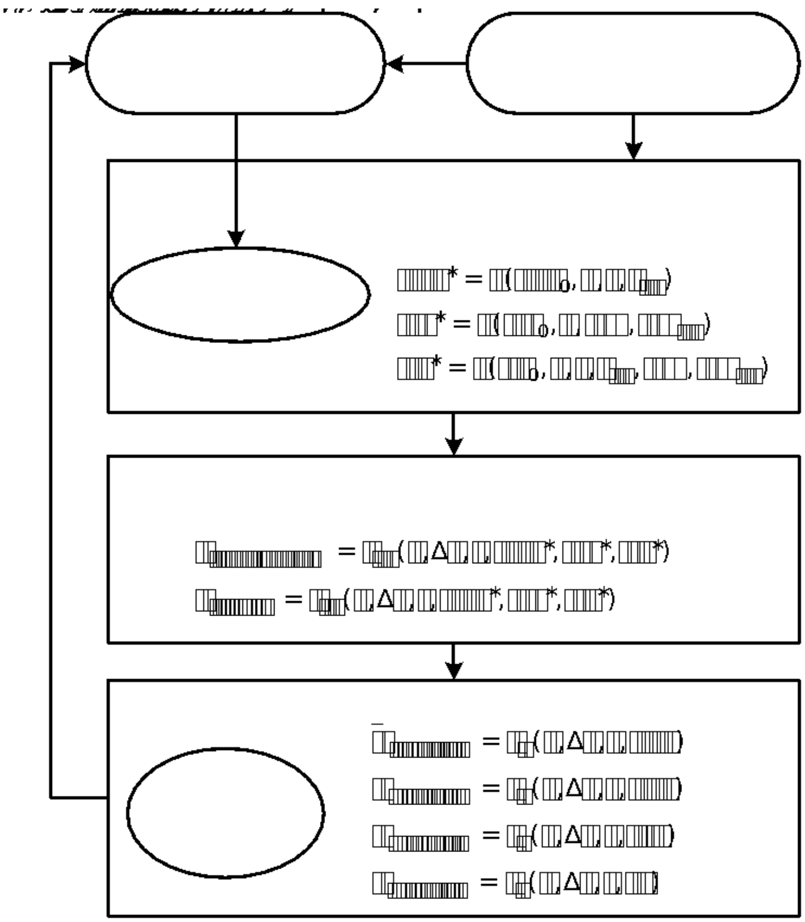

Fig. 1. Methodology framework for identifying optimal ADAS configuration.

2.1 Modeling driver behavior adaptation in the CV environment

The Advanced Driver Assistance System (ADAS) is one of the most important CV safety systems envisioned integrated into the CAVs. A typical ADAS contains functions such as forward collision warning (FCW), queue warning (QW), curve warning (CW), blind spot warning (BSW), cruise control (CC), adaptive cruise control (ACC), intelligent speed adaptation (ISA), and lane departure warning (LDW) [7, 8,9]. As Table 1 shows, these functions are related to drivers' perception-reaction time (PRT), desired speed (DS), desired headway (DH), estimation errors (EE), mental effort (ME), and attention (ATT). Among them, the CV's impact on PRT, DS, and DH can be quantified based on the objective testing results of the existing simulator and field CV studies. CV's impact on EE, ME and ATT largely relies on users' subjective ratings. It is difficult to incorporate directly the subjective results into the state-of-the-art traffic flow models. For this reason, only the PRT, DS, and DH are considered for the CV effectiveness modeling. The remaining behavior parameters will be incorporated into the modeling framework as supporting data becomes available in the future.

Previous studies reveal that the PRT reduction of an ADAS-equipped driver could be in a range of 10% to 50% [10,7,11]. Such a variation is assumed to be associated with drivers' compliance level to the ADAS information. In this study, a compliance index σ is assigned to each of the modeled drivers. The index is a random integer that ranges between 0 and 100. A driver with a compliance index of 0 completely ignores the information sent by the ADAS, whereas a driver with a compliance index of 100 completely follows the ADAS instructions. In addition, the impact of one ADAS warning message on driving behavior is not likely to last for a long time. A driver might stay alerted for a while after receiving the ADAS message, and then gradually resumes her normal driving pattern (**Fig. 2**).

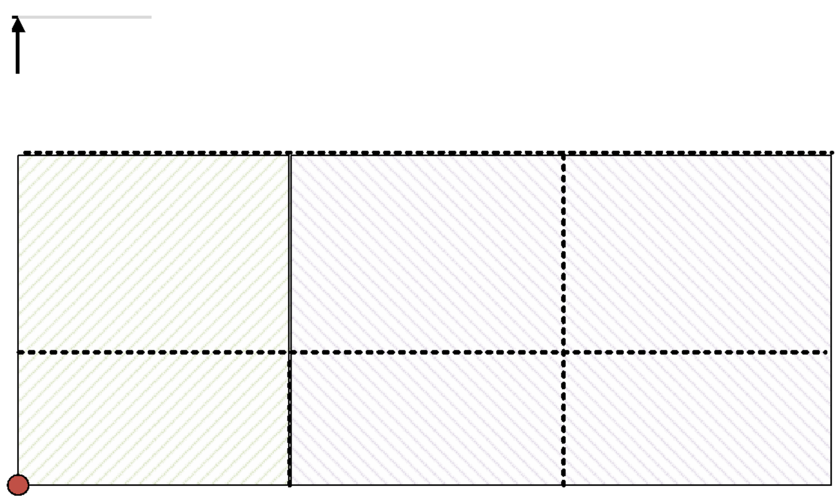

Fig. 2. Duration of ADAS impact.

2.2 Incorporating CV-affected driver behaviors into car-following model

These ADAS-affected driving behaviors are incorporated into the Intelligent Driver Model (IDM) [12] in the form of desired headway parameter, desired speed parameter and perception-reaction time parameter, respectively. The modified IDM is mathematically represented by the following equations:

$$\dot{\square}(\square + \square\square\square^*) = \square\left[1 - \left(\frac{\square(\square+\square\square\square^*)}{\square\square^*}\right)^{\square} - \left(\frac{\square^*(\square(\square+\square\square\square^*),\Delta\square(\square))}{\square(\square)}\right)^{\square}\right] \quad (1)$$

$$\square^*(\square,\Delta\square) = \square_0 + \square\square\square\left(0, \square\cdot\square\square^* + \frac{\square\Delta\square}{2\sqrt{\square\square}}\right) \quad (2)$$

where $\square$ is time interval; $\square$ is the maximum acceleration; $\square$ is the comfortable deceleration; $\square_0$ is the minimum spacing; and α and β are model parameters. After incorporating the PRT term into the IDM, the modeled vehicles will be allowed to involve in collisions. However, realistic modeling of traffic collisions is beyond the capability of the modified IDM. Hence these artificial collisions are removed from the numeric simulation algorithm. To this end, a vehicle trajectory check module is developed in this study to screen the trajectory of individual modeled vehicle in each simulation time step. If a vehicle is about to collide with another vehicle in the next time step, the PRT term is temporarily relaxed from Equation (1) and the acceleration is updated without delay term. As a result, the undesirable collisions are avoided.

2.3 Measuring safety impact of CV with surrogate safety measures

The occurrence of conflicts is identified by using the time-to-collision (TTC), as the time remaining until a collision occurs between two vehicles only when their collision course and speed difference are maintained [13]. In the simulation, the TTC is monitored continuously between a subject vehicle and a leading vehicle. If at some time the TTC of a subject driver drops below a threshold TTC, it indicates the start of a conflict. As the TTC rises above the threshold again, the conflict is ended and the collision is avoided. When the relative acceleration between the subject (F) and the leading (L) vehicles is not equal to zero, the TTC is computed as [6]

$$TTC = \begin{cases} t_1 & 0 < t_1 < t_2 \\ t_2 & 0 < t_2 \leq t_1 \\ t_1 & t_1 > 0 \text{ and } t_2 \leq 0 \\ t_2 & t_2 > 0 \text{ and } t_1 \leq 0 \end{cases} \quad (3)$$

$$t_1 = \frac{-\Delta v - \sqrt{\Delta v^2 + 2\Delta a D}}{\Delta a};\ t_2 = \frac{-\Delta v + \sqrt{\Delta v^2 + 2\Delta a D}}{\Delta a} \quad (4)$$

where D is the spacing between the leading vehicle and the subject vehicle; v represents speed; a represents acceleration; Δv is the relative speed, $\Delta v = v_F - v_L$; and Δa is the relative acceleration, $\Delta a = a_F - a_L$. If the relative acceleration is zero, the TTC is mathematically given as:

$$TTC = \begin{cases} \frac{D}{\Delta v}, & v_L < v_F \\ \infty, & \text{otherwise} \end{cases} \quad (5)$$

The threshold TTC is 1.5 seconds, as recommended by Gettman et al. [5]

In addition to the TTC, two TTC-based measures are adopted in this study to capture more detailed information of individual traffic conflicts. Particularly, the duration of conflicts is indicated by the time exposed TTC (TET) presented in Minderhoud and Bovey [14]. It is given as:

$$TET = \sum_{t=0}^{T} \delta_t \cdot \tau \quad \delta_t = \begin{cases} 0, & \text{otherwise} \\ 1, & 0 \leq TTC_t \leq \text{threshold } TTC \end{cases} \quad (6)$$

where τ is the time step; and T is the total number of time steps. The TET measures a drivers' the level of exposure to the traffic conflicts over a period of time. It represents the total time that a subject driver has TTC lower than the threshold TTC during a period of time. A small TET indicates that the subject driver only exposes to risky traffic conditions in a short period of time.

Another TTC-based measure, termed as the time integrated TTC (TIT), represents the area between a TTC profile and the threshold TTC [14]. The TIT not only considers the duration of conflicts, but also depicts how close each conflict is to collision (a collision occurs when TTC = 0). The larger the TIT is, the bigger risk the subject driver has over a study time period. The TIT is computed by the following equation:

$$TIT = \sum_{t=0}^{T} \delta_t \cdot (TTC^* - TTC_t) \cdot \tau \quad (7)$$

The above TTC-based indicators depict duration and risk level of traffic conflicts. The kinetic energy changed in the course of a conflict is adopted to measure the level of severity if the observed conflicts turn into crashes. Kinetic indicator termed as crash index (CI) proposed by Ozbay et al. [6] is used in this study:

$$CI = \underline{m} \frac{(\Delta v + \Delta a \cdot TTC) \cdot [(v_F + a_F) + (v_L + a_L) \cdot TTC]}{2} \cdot \frac{1}{TTC} \quad (8)$$

where $\underline{m}$ is the average weight of modeled vehicles. The CI reflects the energy exchanged per unit time during a conflict. To compute the total energy exchanged in conflicts, the following equation is used:

$$\Delta E = \sum_{t=0}^{T} \delta_t \cdot CI \cdot \tau \quad (9)$$

2.4 Case Study

A 900-meter freeway segment at northbound I-71 freeway close to Exit #12 in the Greater Cincinnati area, Ohio is taken as the study site. The IDM calibration and validation is carried out following the procedure developed by Park and Won [15]. The ADAS effects on the surrogate safety measures are generalized using regression analysis. The first effect (i.e., conflict frequency) is represented by the number of conflicts per hour; and the second effect (i.e., conflict intensity) is represented by the average duration, TIT and energy exchanged of individual conflict. Simple linear regression models are capable of depicting the functional relationship between these factors and the surrogate safety measures (i.e., hourly TET, TIT and Δ□). In the regression model, the first effect variable or "factor" (e.g., *Nc*, $\underline{□}_{□}$ in Table 1) is more important than the second for improving the system safety performance. For example, a unit decrease of the standardized hourly conflict would result in about 0.82 unit decrease of the standardized hourly TET and TIT. On the other hand, a unit decrease of the standardized average conflict duration can only result in 0.21 unit decrease of the standardized hourly TET; and a unit decrease of the standardized average TIT per conflict can result 0.23 unit decrease of hourly TIT. The first factor has an impact 4 times stronger than the second effect. For the reduction of the hourly kinematic energy exchanged in conflicts, the two general factors are similarly effective. A unit decrease of the standardized hourly conflict and average energy exchange per conflict would lead to 1.56 and 1.17 unit decrease of the standardized hourly energy exchanged, respectively. For the effect on Δ□, it is found that the two factors also have a compounding effect because of 0.70 coefficient in the factor $□_{□} \cdot \underline{□}_{□}$.

Table 1: Impact of ADAS effects on levels of surrogate safety measures.

Impact on □□□			**Impact on □□□**			**Impact on Δ□**		
Factor	**Coef.**	**S.E.**	**Factor**	**Coef.**	**S.E.**	**Factor**	**Coef.**	**S.E.**
$□_{□}$	0.82	0.01	$□_{□}$	0.82	0.01	Intercept	0.32	0.01
$\underline{□}_{□}$	0.21	0.01	$\underline{□□□}_{□}$	0.23	0.01	$□_{□}$	1.56	0.02
						$\underline{□}_{□}$	1.17	0.02
						$□_{□} \cdot \underline{□}_{□}$	0.70	0.02
R^2 = 0.996			R^2 = 0.994			R^2 = 0.990		

To quantify the impact of the ADAS-affected behavior parameters, the 2^3 factorial design is adopted. The ADAS effect on PRT, DH, and DS is analyzed in the role of reducing conflict frequency and decreasing conflict intensity by the average PRT of modeled drivers (high level 1.2 s and low level 0.6 s), the average DS (high level 35 m/s and low level 27 m/s), and the average DH (high level 1.2 s and low level 0.7 s).

The hourly TIT is influenced by PRT, DH and DS (**Fig. 3**). There are 1 thin line and 1 thick line between TIT and DS; 2 thin lines between TIT and DH; and 1 thin line and 3 thick lines between TIT and PRT. Thus the PRT plays the most important role in terms of impacting the hourly TIT; the DH is least important. If a CV safety system is being developed to improve the hourly TIT, the system should be designed to control the PRT as a primary factor over the other two candidate behavior parameters.

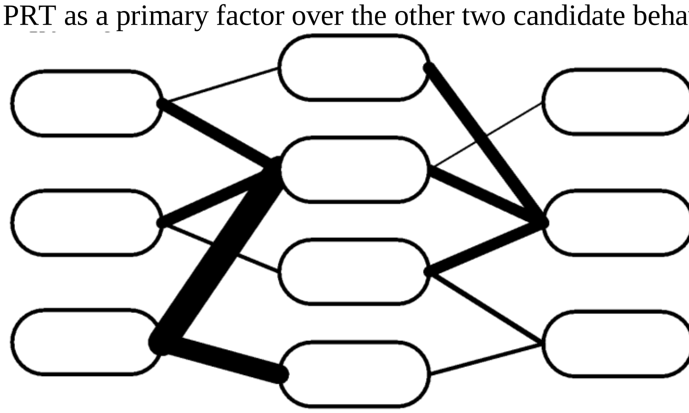

Fig. 19. Cause-and-effect relationship among surrogate safety measures and behavior parameters.

5. Conclusion

This research quantifies the impact of the CV-affected driving behaviors on the safety performance of a freeway facility in a case study. At an increasing the penetration rate of the CV, the average behavior parameters of the driver population rapidly approaches to the desired behavior levels set by the CV system. The surrogate safety measures improve following the same rapid trend with time. It suggests that a strong cause-and-effect relationship exists between the CV-equipped drivers' behavior adaptation and the improvement of the safety performance. The analyzed ADAS is capable of reducing drivers' PRT and DS and increasing the DH. The reduction of PRT and DS is responsible for the decrease of traffic conflict frequency. The reduction of PRT results in decrease of the average duration of conflicts and the average kinematic energy exchanged in conflicts. The adaptation of PRT and DH leads to lower average TIT, implying a reduced risk level of conflicts. Furthermore, the contribution of the CV-affected behaviors is examined in reducing the surrogate safety measures. The quantified contribution are used to determine the rank of the behavior parameters. It is determined that to efficiently improve the safety performance, the envisioned CV safety systems should be designed to affect the high rank behavior parameters such as PRT.

The presented methodology is not exclusive to the ADAS function evaluated in this study. The open framework is capable of incorporating other CV systems, as long as their impact on driving behavior adaptation is quantified. By using the framework, systematic analysis can lead to a foundation to 1) evaluate the effectiveness of envisioned CV safety systems before they are widely deployed in the field; 2) identify key ADAS-affected behavior parameters that can lead to the greatest safety improvement; and 3) promote successful deployment of the advanced technologies into the existing highway transportation systems.

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