Accident Analysis and Prevention 113 (2018) 149–158

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

Assessing rear-end collision risk of cars and heavy vehicles on freeways using a surrogate safety measure

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ARTICLE INFO

Keywords:
Rear-end collision
Collision risk
Surrogate safety measure
Crash potential index
Heavy vehicle
Car-following behavior

ABSTRACT

This study analyzes rear-end collision risk of cars and heavy vehicles on freeways using a surrogate safety measure. The crash potential index (CPI) was modified to reflect driver's reaction time and estimated by types of lead and following vehicles (car or heavy vehicle). CPIs were estimated using the individual vehicle trajectory data from a segment of the US-101 freeway in Los Angeles, U.S.A. It was found that the CPI was generally higher for the following heavy vehicle than the following car due to heavy vehicle's lower braking capability. This study also validates the CPI using the simulated traffic data which replicate the observed traffic conditions a few minutes before the crash time upstream and downstream of the crash locations. The observed data were obtained from crash records and loop detectors on a section of the Gardiner Expressway in Toronto, Canada. The result shows that the values of CPI were consistently higher during the traffic conditions immediately before the crash time (crash case) than the normal traffic conditions (non-crash case). This demonstrates that the CPI can be used to capture rear-end collision risk during car-following maneuver on freeways. The result also shows that rear-end collision risk is lower for heavy vehicles than cars in the crash case due to their shorter reaction time and lower speed when spacing is shorter. Thus, it is important to reflect the differences in driver behavior and vehicle performance characteristics between cars and heavy vehicles in estimating surrogate safety measures. Lastly, it was found that the CPI-based crash prediction model can correctly identify the crash and non-crash cases at higher accuracy than the other crash prediction models based on detectors.

1. Introduction

As economy is globalized in recent few decades, demand for freight transportation has dramatically increased. As more heavy vehicles shared the same road with passenger cars, interactions between cars and heavy vehicles also increased. This results in higher number of heavy vehicle-involved crashes which are more likely to cause fatality or severe injury. In Canada, 524 people died and 11,574 were injured in heavy vehicle-involved crashes in 2001 (Mayhew et al., 2004). This accounts for 20% of fatalities and 5% of reported injuries due to crashes on roadways. In the U.S., 4186 large trucks and buses were involved in fatal crashes in 2013, and large truck and bus fatalities per 100 million vehicle miles traveled by all motor vehicles remained steady at 0.142 from 2012 to 2013 (Federal Motor Carrier Safety Administration, 2014).

To identify the factors contributing to heavy-vehicle-involved crashes, historical crash data have been collected and crash frequency has been predicted using statistical models. However, the development of crash prediction models requires a long period of crash data collection due to infrequent occurrence of crashes (Gettman et al., 2008). Moreover, this method is not effective in preventing crash occurrence since the locations of high risk of collision can only be identified after high crash frequencies are observed (Gettman et al., 2008).

In contrast, the conflict-based studies using surrogate safety measures predict the collision risk based on the individual vehicle movement data which can be collected in a shorter time period. Unlike the crash-based studies, this method can also proactively mitigate the collision risk before more serious safety problems occur. Surrogate safety measures are typically estimated using the lead and following vehicles' speeds and acceleration, and their spacing.

However, in the estimation of surrogate safety measures, the types of lead and following vehicles such as vehicle size and acceleration/deceleration capability have not been explicitly investigated. For instance, heavier vehicles have lower deceleration capability than lighter vehicles. Thus, if the lead vehicle stops, it takes longer time for the following heavy vehicles to decelerate to avoid a collision than light vehicles. Consequently, the collision risk will be higher for heavy vehicles. For this reason, heavy vehicle drivers tend to maintain longer

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https://doi.org/10.1016/j.aap.2018.01.033
Received 19 April 2017; Received in revised form 16 December 2017; Accepted 25 January 2018

spacing with the lead vehicle than car drivers. On the other hand, due to the difference in the height of the driver position between cars and heavy vehicles, heavy vehicle drivers generally have a better view of the road and can adjust speeds faster than car drivers.

Also, the type of lead vehicle affects the following vehicle driver's sight. Larger lead vehicles are more likely to obstruct the following smaller vehicle driver's sight. In this situation, the following vehicle drivers tend to reduce speed to maintain longer spacing with the lead vehicle and increase their sight distance. Clearly, the types of lead and following vehicles affect the behavior of the following vehicle's driver and the collision risk. Thus, these effects must be captured in the estimation of surrogate safety measures.

Conventionally, surrogate safety measures have been estimated using the microscopic traffic simulation model and these simulated surrogate safety measures have been validated by comparing them with the observed crash frequency (Shahdah et al., 2015; Essa and Sayed, 2015; Ariza, 2011). However, the correlation between the simulated surrogate safety measures and crash frequency is an insufficient evidence of validity since most of the correlation comes from exposure (traffic volumes). Thus, the correlation does not guarantee that the variability of frequency of crashes observed in the real world under the same exposure is properly reflected in the simulated surrogate safety measures. Moreover, the crash frequency data do not include the events with high collision risk which did not lead to a crash (Cunto et al., 2009). Thus, Cunto et al. (2009) proposed to validate surrogate safety measures by comparing them between the traffic conditions a few minutes before the time of actual crashes (crash case) and the normal traffic conditions (non-crash case). They found that the surrogate safety measure was higher for the crash case than the non-crash case. However, they did not validate the surrogate safety measure for the different types of lead and following vehicles.

This study develops a more elaborate surrogate safety measure for rear-end collision risk called the crash potential index (CPI) which was originally proposed by Cunto and Saccomanno (2008). The objectives of this paper are to 1) develop a modified CPI which accounts for the difference in driver behavior and vehicle performance between cars and heavy vehicles, 2) compare the CPIs among different types of lead and following vehicles, and 3) validate the CPIs using the observed traffic data at the time of crashes and during normal traffic conditions.

2. Literature review

To estimate crash risk, real-time crash prediction models have been developed using loop detector data and historical crash records in the past studies. These studies hypothesized that short-term traffic flow changes (e.g., speed variation) immediately before crash occurrence contribute to crash risk. For instance, Abdel-Aty et al. (2004) predicted the crash likelihood using real-time traffic data extracted from loop detectors 5–10 min before the crash. Furthermore, the authors investigated real-time likelihood of rear-end crashes (Pande and Abdel-Aty, 2006a) and lane-change crashes (Pande and Abdel-Aty, 2006b). Similarly, Hossain and Muromachi (2011, 2013) predicted crash risk for different locations (basic freeway segments and vicinity of ramp) and different types of crash (rear-end and sideswipe). Xu et al. (2013a,b) also predicted crash risk for different crash severity levels (fatal, injury, and property damage only) and weather conditions (clear, rainy, and reduced visibility).

Although these models show good performance in crash prediction, the detector data have some inherent limitations. First, the data cannot capture individual vehicles' movements and their interaction although these factors are important for predicting risk of collision between two vehicles. For instance, it is possible that the high crash risk events (e.g., very short spacing, very high relative speed) occurs at one time instant. Although this event can lead to crash occurrence, the aggregated traffic data from the detectors cannot capture such instantaneous events that occur to individual vehicles. Second, the detectors cannot identify the high crash risk events which occur at the location where the detectors are not installed. Consequently, the past crash prediction models based on detector data have the same limitations.

To estimate crash risk for individual vehicles, various surrogate safety measures have been developed using vehicle trajectory data in the past. For instance, Time-to-collision (TTC) has been used to estimate the rear-end collision risk between two vehicles in the same lane (Hayward, 1972; Hyden, 1987). Gettman and Head (2003) defined TTC as the time it takes for the following vehicle to reach the position of the lead vehicle if the lead vehicle stops and the following vehicle's speed remains the same.

Bachmann et al. (2012) revised this definition of TTC assuming that the lead vehicle also continues moving at the present speed and on the same trajectory. Some researchers defined TTC considering both gap and speed difference between two vehicles (Minderhoud and Bovy, 2001; Vogel 2003; Astarita et al., 2012). In their definitions, TTC is calculated using the distance between the rear end of the lead vehicle and the front end of the following vehicle instead of the front-to-front distance. Thus, this TTC considers actual spacing between two vehicles. However, this TTC can be calculated only if the following vehicle's speed is higher than the lead vehicle's speed. To overcome this limitation of the conventional TTC, Ozbay et al. (2008) proposed the modified TTC (MTTC) which estimates the collision risk even when the following vehicle speed is lower than the following vehicle speed. MTTC is determined based on both relative speed and relative acceleration of two successive vehicles.

Post-encroachment time (PET) has also been used to estimate the rear-end collision risk. PET is defined as the difference between the time when the lead vehicle last occupied a position and the time when the following vehicle first reached the same position (Gettman and Head, 2003). Unlike TTC, PET is an observed value which considers the speed and acceleration variability of the two vehicles during the conflict. Most drivers of the following vehicles will decelerate to maintain sufficient safety distance when the gap with the lead vehicle decreases. Due to this driver's speed adjustment, the value of PET is generally longer than that of TTC.

Another surrogate safety measures called "the deceleration to avoid crashes (DRAC)" is defined as the minimum deceleration rate of the following vehicle to timely stop behind the lead vehicle as follows:

$$DRAC(t) = \frac{(V_L(t) - V_F(t))^2}{2(X_L(t) - X_F(t) - L_L)},\ V_F(t) > V_L(t) \tag{1}$$

where DRAC(t) is the DRAC at time t; $X_L(t)$ and $X_F(t)$ are the positions of the lead and following vehicles at time t, respectively; $V_L(t)$ and $V_F(t)$ are the velocities of the lead and following vehicle at time t, respectively; and L_L is the length of the lead vehicle. Lower TTC, lower PET and higher DRAC represent the higher probability of rear-end collision risk.

Cunto and Saccomanno (2008) developed the crash potential index (CPI) using DRAC and maximum available deceleration rate (MADR) or braking capacity of the following vehicle. The CPI is defined as the probability that the following vehicle's DRAC exceeds MADR. The CPI for vehicle i is calculated using the following equation:

$$CPI_i = \frac{\sum_{t=0}^{N} \Pr(DRAC_i(t) > MADR_i(t)) \times \Delta t}{T} \tag{2}$$

where $MADR_i(t)$ are the MADR of the vehicle i at time t; N is the total number of time intervals; Δt is the observation time interval and T is the total observation time period (T = N × Δt). $MADR_i(t)$ varies in different surface conditions of the roadway (wet or dry) and vehicle mechanical characteristics (braking system). Due to these variations, MADR was assumed to follow the truncated normal distribution (American Association of State Highway and Transportation Officials (AASHTO, 2004; Cunto and Saccomanno, 2008; Weng and Meng, 2011).