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Risk perception and the warning strategy based on microscopic driving state

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ABSTRACT

The paper aimed to explore the relationship between risks and individuals' driving states and then design an efficient method to help drivers avoid high risks. The relationship between risks and individuals' driving states was deeply studied first. Microscopic driving states were categorized into different clusters, and it was found that the risks are distinct in different clusters and a specific driver might experience different risks in car-following process. Then, according to these findings, a risk warning strategy was designed to help drivers avoid high risks. The risk warning is active when the risk is higher than its threshold. The Helly models were used to mimic the drivers' reaction to study the influence of the warning strategy. Simulation results showed that with the consideration of the risk warning, the spacing obviously increases, and the oscillations of velocity and acceleration are significantly shrunk, and risks in the driving process dampen down. Because drivers can perceive high risks during the driving process, and then appropriately change their car-following decisions to avoid high risks. These findings are helpful to improve driving behaviors and promote traffic safety.

1. Introduction

With the rapid increase of motorized vehicles, traffic safety issues have become increasingly prominent, which not only threaten people's lives, but also lead to enormous economic losses. Generally, risks for driving behaviors are strongly related to drivers' road safety attitude and risk perception. Risk perception can help to avoid the occurrence of traffic accidents and affect driver's attitude (Ram and Chand, 2016). Furthermore, some studies (Hoedemaeker and Brookhuis, 1998; Jonah et al., 2001; Lewis-Evans and Charlton, 2006; Thomas and Walton, 2007; Koornstra, 2009; Martha and Delhomme, 2009; Joubert et al., 2016), showed that drivers' risk perception played important roles on their driving behaviors. Therefore, it is essential to understand how traffic risks are related to driving behaviors and how to help drivers perceiving risks (Cristea and Gheorghiu, 2016).

The relationships between risks and traffic states have been widely studied in both macroscopic level and microscopic level. From macroscopic perspective, the relationship between crash count, traffic parameters and road geometry parameters has been widely studied in past decades (Lord and Mannering, 2010). Researchers have been explored the relationship between historical crash data and traffic volume, speed, and other traffic characteristics (Lee and Abdel-Aty, 2005, 2008; Wong et al., 2007; Wang et al., 2009). Belmont and Forbes (1953) pointed out that the accident rate increases linearly with traffic flows. Furthermore, Ceder (1982) investigated the difference under free flow and congested flow. It was revealed that the accident rate is a U-shaped function with the flow in free flows, whereas has a sudden increase with the flow under congested conditions. Belmont and Forbes (1953) also found that speed and occupancy have important influences on the accident rate, and the higher the speed the more serious accidents. Gargoum and El-Basyouny (2016) explored the relationship between traffic characteristics and collisions. They found that average speed, volume, segment length, medians and horizontal curves all significantly influence collision frequency, and other variables have indirect effects on safety by influencing speeds. Gitelman et al. (2017) studied the relationship between travel speeds and accidents on single-carriageway roads. Negative binomial statistical models were used to fit the relationship between injury accident counts and other factors, and the results showed that there was a positive relation between mean speeds and accidents. Many different models have been developed to describe the relationship between crash data and various influences factors. Poisson regression model is used as a starting point for crash-frequency analysis (Jovanis and Chang, 1986; Miaou, 1994). And then some extended methods have been applied in crash-frequency modeling, including Poisson-gamma/negative binomial models (Lord, 2006), Poisson-lognormal models (Lord and Miranda-Moreno, 2008), Zero-inflated models (Shankar et al., 2003), Conway–Maxwell–Poisson model (Lord et al., 2008), Gamma model (Oh et al., 2006) etc. Macroscopic states are averaged by using traffic variables over a period of time, which cannot reflect instant changes of individual behaviors. In

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driving process, risks are closely linked with individual behaviors. For example, a large number of traffic accidents can be ascribed to inappropriate driving behaviors. Therefore, it is necessary to analyze risks based on individual driving states from microscopic perspective to reduce risks and improve traffic safety.

From microscopic perspective, car-following models based on risk perception have been developed to describe driving behaviors and understand traffic discipline on roads. Generally, these models are formulated to reflect drivers' decision-making process, based on individual driving states, e.g. vehicles' position, velocity, relative velocity, relative spacing, and acceleration, etc.. Chandler et al. (1958) utilized relative speed as stimulus to develop a linear stimulus-response model. Bando et al. (1995) presented the optimal velocity model to describe the driving adjustment of drivers according to the difference between their current velocity and the desired velocity. Li et al. (2007) formulated an empirically desired headway (EDH) model by proposing the EDH at its current velocity. Additionally, some other microscopic variables, as the acceleration, velocity, relative spacing, were used to model car-following dynamics (Gong et al., 2008; Newell, 2002; Andersen and Sauer, 2007; Gazis et al., 1961; Gipps, 1981). All these models tried to capture the detail driving behaviors aiming to well depict the moving dynamics of vehicles. However, Lu et al. (2012, 2013) pointed out that these models cannot precisely describe how drivers perceive the driving risk in car-following process and what can be used to evaluate their risk level. Wang et al. (2016) also stated that these models cannot reflect interactions among traffic factors and driving safety. To measure driving safety, some safety distance models for the longitudinal movement were presented (Abdel-Aty et al., 2006; Caliendo et al., 2007), e.g., time to collision (TTC) (Kiefer et al., 2006), time headway (TH), and safety margin (SM) etc.. TTC was widely used to build up collision avoid system (Horst and Hogema, 1993), or evaluate the risk level (Miller and Huang, 2002). Also, the safety distance was used to access the risk level in car-following, e.g. minimum gap and the actual gap. Gipps (1981) and Treiber et al. (2000) proposed car-following models by considering actual gap and desired minimum gap. In intelligent-driver models (IDM), both actual gap and desired minimum gap were used to determine vehicles' dynamics, which were combinations of comfortable braking deceleration, minimum spacing, maximum acceleration, and desired time headway. Lu et al. (2012, 2013) proposed a new method to formulate car-following behaviors by using desired safety margin. Huang et al. (2014) evaluated the influence of time-reminder strategies on the signalized intersection's safety level. Zheng and He (2015), Zheng et al. (2016) proposed a car-following model with consideration of visual imaging. Wang et al. (2013, 2014, 2015, 2016) utilized various traffic factors in driving safety field to avoid collision for automated vehicles. These methods could evaluate potential driving risk in real traffic scenarios. However, most of these methods are limited to scenarios with automated vehicles. As known, there is a long way to enter the times with completely automated vehicles. At the same time, the collision avoidance algorithm is complicated for drivers to determine how to perceive traffic safety and adjust their behaviors. Machado-León et al. (2016) pointed out that the relationship between risk perceptions and people's risky driving behaviors has not been disclosed completely, and they studied the potential effect of risky driving behaviors on drivers' perceptions of crash risk and perception differences among different drivers. Eboli et al. (2017) found that road accidents are mainly ascribed to the distorted perception of risk level, and raising the awareness of drivers is useful to make individual driving safer. Thus, it is essential to help drivers perceive risks, especially under dangerous condition, and then they can adjust their car-following behaviors to avoid high risks.

In this paper, the relationship between risks and individuals' driving states is deeply studied first. Then, according to the relationship, a risk warning strategy based on Helly models is designed to help drivers avoid high risks. Finally, the Helly models are used to mimic the drivers' reaction to study the influence of the warning strategy.

The paper is organized as follows. Firstly, traffic data used here and risk indicators are introduced in Section 2. The comparison between individuals and the average level is made. Then, in Section 3, microscopic driving states are categorized into different clusters, which have distinct risk level. In Section 4, the Helly model is briefly reviewed and calibrated by using MCMC(Markov chain Monte Carlo) method. And a risk warning term is introduced in the Helly model to mimic drivers' response to the risk warning. Finally, the conclusions are summarized in Section 5.

2. Traffic data and risk indicators

2.1. Traffic data

Traffic data used in this paper come from the NGSIM (Next Generation SIMulation) project of the FHWA (FHWA, 2008). The data used in this paper is extracted from the video images of the Amorieville I-80 in California and gathered from 5:15 p.m. to 5:30 p.m. in April 13, 2005. The road is about 500 m long and has seven lanes, including lane 1 for a high-occupancy vehicle (HOV), lane 7 for the ramp, lane 6 connected to the ramp, and lanes 2–5 for the ordinary lane. Traffic data mainly includes vehicle ID, lane number, time, front and rear vehicle speed, acceleration, vehicle length and head spacing.

2.2. Analysis of potential traffic risks

Potential traffic risks are measured by risk indicators. At present, the commonly used indicators are time-to-collision (TTC), headway time (TH), safety margin (SM), time to accident (TTA), post encroachment time (PET), deceleration to safety time (DTS), and deceleration rate to avoid crash (DRAC), etc. (Andrew, 2011; Lu et al., 2012). Here, TTC and SM are used to assess potential risks.

(1) TTC is defined as the time that remains until a collision between 2 vehicles will occur if the collision course and velocity difference are maintained.

$$TTC_i(t) = \frac{d_i(t)}{v_i(t) - v_{i-1}(t)}, \ \forall \ v_i(t) > v_{i-1}(t) \tag{1}$$

where $d_i(t)$ is the spacing between vehicle i and its front vehicle i - 1 at time t, and $v_i(t)$ is the speed of vehicle i at time t. $v_i(t) - v_{i-1}(t)$ is called as velocity difference, denoted by $\Delta v_i(t)$. TTC approaches to infinity if $\Delta v_i(t)$ is equal to or very close to 0. Therefore, 1/TTC is commonly used instead of TTC. 1/TTC is greater than 0, indicating that there are potential risks. And the greater the 1/TTC, the higher the potential risks. 1/TTC is less than or equal to 0, indicating that there is no risks.

(2) SM is to determine level of risk by using actual gap and minimum safe gap (Lu et al., 2012).

$$SM_i(t) = 1 - \left\{\frac{\tau_1 \cdot v_i(t)}{d_i(t)} + \frac{[v_i(t) + v_{i-1}(t)][v_i(t) - v_{i-1}(t)]}{1.5g \cdot d_i(t)}\right\} \tag{2}$$

where τ_1 is response time of the brake system, which is distinct under different situation, and here $\tau_1 = 0.15$ s. g is the acceleration of gravity. A large SM indicates that the driver has enough time to respond its front car. The SM is less than 1, meaning that there are potential risks. The smaller the SM, the greater the potential risks.

Fig. 1 reveals the variations of risk indicators with time for both macroscopic and microscopic states. Solid circles represent average risks, which is averaged by all vehicles within 120s-interval. Hollow circles represent potential risks for individual vehicles. The average 1/TTC is close to zero and its fluctuation is very small. While the 1/TTC for individuals has large fluctuations. The maximal 1/TTC is about 1, and the minimum is about -0.8. The average SM remains near 1, whereas the SM for microscopic individuals appears much smaller