Accident Analysis and Prevention 123 (2019) 159–169

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

# Utilizing UAV video data for in-depth analysis of drivers' crash risk at interchange merging areas☆

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ARTICLE INFO

*Keywords:*
Merging behavior
Crash risk
Interchange
UAV

ABSTRACT

The interchange merging area suffers a high crash risk in the freeway system, which is greatly related to the intense mandatory merging maneuvers. Ignoring such correlation may result in limited and biased conclusions and inefficient countermeasures. Recently, the availability of unmanned aerial vehicle (UAV) provides us an opportunity to collect individual vehicle's data to conduct traffic analysis at the microscopic level. Hence, this paper contributes to the literature by proposing a new framework to analyze crash risk at freeway interchange merging areas considering drivers' merging behavior. The analysis framework is conducted based on individual vehicle data from UAV videos. A multilevel random parameters logistic regression model is proposed to investigate each driver's merging behavior in the acceleration lane. The model could identify the impact of different factors related to traffic and drivers on the merging behavior. Then, the crash risk between the merging vehicle and surrounding vehicles is calculated by incorporating the time-to-collision (TTC) and the output of the estimated merging behavior's model. The results suggest that the proposed method provides more valuable insights about the crash risk at interchange merging areas by simultaneously considering the merging behavior and the safety measure. It is concluded that the merging speed, driving ability (e.g., lane change confidence, lane-keeping instability), and the merging location can affect the crash risk. These results can help traffic engineers propose efficient countermeasures to enhance the safety of the interchange merging area. The results also have implications to the design of merging areas and the advent of connected vehicles' technology.

## 1. Introduction

The interchange merging area plays a vital role in providing access to freeways with an uninterrupted traffic flow. A bottleneck could occur if there is a crash at the interchange merging area. Evidence showed that interchange merging areas have significantly higher crash risk in the freeway system regarding crash frequency and severity (Ahammed et al., 2008; Firestine et al., 1989). One possible reason of such high crash risk is that drivers need to conduct mandatory merging maneuvers to get into the freeways (Ahammed et al., 2008; Yang and Ozbay, 2011). Hence, it is important to investigate drivers' merging behavior and crash occurrence mechanisms to help enhance the safety and prioritize the countermeasures of the interchange merging areas.

Numerous studies have been conducted to investigate the crash occurrence at freeway interchange merging areas using two approaches. One is to develop crash prediction models based on historical crash data to examine the effect of different factors including speed, volume, weather, and road conditions on crash occurrence (Eustace et al., 2015; Lee and Abdel-Aty, 2009; McCartt et al., 2004; Mergia et al., 2013; Sarhan et al., 2008). Such approach could suffer from several problems such as underreporting, misclassification, and inaccurate location. The inaccurate location problem could become even worse at interchange areas. For example, a study conducted in Missouri showed that the geoinformation of nearly 70% crashes at interchange areas was not correct (Sun et al., 2016). Besides, since the studies were conducted with aggregated data, it is hard to investigate the impact of drivers' behavior on crash risk. In addition, it would be difficult to rapidly evaluate the recent treatments due to the lack of after-treatment crash data, which requires observations of a long period (Fu et al., 2018; Wu et al., 2018). The other approach is using

☆ This paper has been handled by associate editor Tony Sze

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https://doi.org/10.1016/j.aap.2018.11.010
Received 16 June 2018; Received in revised form 8 November 2018; Accepted 10 November 2018
Available online 01 December 2018

individual vehicle data (e.g., location and speed of each vehicle) to investigate drivers' merging behavior (Chu et al., 2017; Kondyli and Elefteriadou, 2011; Sun et al., 2014; Wan et al., 2017) and safety (Fan et al., 2013; Li et al., 2016, 2017; Oh and Kim, 2010). However, most of these studies conducted the analysis of drivers' behaviors and safety, separately. Since drivers should select gaps they think are safe to merge, there should be a correlation between the driver's merging behavior and safety (Kim et al., 2016). Ignoring such correlation may result in limited and biased conclusions and inefficient countermeasures. Hence, the current study aims to contribute to the literature by proposing a framework to analyze mandatory-lane-change-related crash risk at freeway interchange merging areas with the consideration of drivers' merging behavior.

## 2. Literature Review

In the previous research, several studies have been conducted to investigate traffic safety at freeway interchange merging areas. Bauer and Harwood (1998) developed statistical models to investigate the effects of several factors on crash frequency of interchange ramps and acceleration/deceleration lanes, including annual average daily traffic of ramp and freeway, length of ramp and acceleration/deceleration lanes. McCartt et al. (2004) examined the most common crash types in different parts of freeway interchanges through historical crash data and found that rear-end or sideswipe crashes predominates among vehicles who were entering the freeway. Ahammed et al. (2008) investigated the effects of geometric design, traffic characteristics, and driver's behavior on the crash occurrence in the acceleration lane. Considering the drawbacks of historical crash data, several research efforts have been made to evaluate safety performance with surrogate safety measures. For example, Oh and Kim (2010) used modified time to collision (MTTC) to estimate the crash probability between two adjacent vehicles. Similarly, Yang and Ozbay (2011) used MTTC to evaluate the probabilistic risk of merging vehicles involved in a rear-end crash on freeway merging sections. Fan et al. (2013) conducted a procedure for estimating traffic conflicts at freeway merging areas through VISSIM and surrogate safety assessment models. Li et al. (2016) proposed a new hourly composite risk index (HCRI) based on time to collision (TTC) to evaluate the traffic safety of freeway interchange merging areas. The study concluded that ramp traffic volume and acceleration lane length were significant factors that positively affected HCRI. Li et al. (2017) selected TTC as the surrogate safety measure to evaluate the impact of different car-following types on crash risk at freeway weaving sections. According to previous studies, TTC is a proper measurement to reflect the crash risk.

As mentioned earlier, the intense merging maneuver is a critical reason for an increased potential for traffic collisions at merging areas. Merging vehicles have to complete the merging maneuver in a limited space and time, leading to a high probability of crash risk. The drivers' decision about when and where to complete a merging maneuver would be highly correlated with the crash risk at merging areas. Yang and Ozbay (2011) estimated rear-end crash risk by investigating the potential conflicts caused by the mandatory lane changes of merging vehicles. A risk map was created to show the relationship between the merging location and the crash risk. Although the mandatory lane change behavior was considered, the merging process has been simplified and hence factors which may have significant effects on merging behavior and mandatory-lane-change-related crash risk might not be identified. Hence, an appropriate model to describe the merging behavior at interchange merging areas is crucial for the analysis of merging decision and model-result-based crash risk estimation.

Numerous studies have been conducted to develop models to describe the merging maneuvers. One of the most important techniques is gap acceptance theory, which has been used in many simulation models (e.g., Aimsun and Vissim). A critical gap is defined to compare with an offered gap between merging vehicles and the lead or lag vehicles in the target lane in order to make an accept or reject decision (Ahmed et al., 1996; Kondyli and Elefteriadou, 2011; Marczak et al., 2013; Michaels and Fazio, 1989). However, this assumption is inconsistent with the reality that vehicles may still make a merging maneuver when the offered gap is smaller than critical gap or reject an offered gap when it is bigger than critical gap (Sun et al., 2018). Some studies have classified merging behaviors into different categories according to gap acceptance theory, since the merging process is simplified to a two-step model: selecting an acceptable gap and executing the lane change. For example, Sun et al. (2014) classified merging behaviors as normal (free-flow) lane change, forced lane change, and cooperative lane change. And five discrete choice models (two multinomial logit models and three nested logit models) were developed and compared to understand the merging behavior. Chu et al. (2017) divided vehicles' merging behaviors into three categories: direct merging, yield merging, and chase merging. The authors applied several discrete choice models to investigate the best model and the contributing factors on the selection of merging behavior. The study (Chu et al., 2017) assumed that merging drivers make instantaneous decisions at a fixed merging point. However, the merging process should be a continuous decision making process since drivers could choose merge or not merge at each time step during the entire merging duration. Hence, such merging behavior could be considered as a sequential choice process as suggested in previous research (Wan et al., 2017).

Except for model studies, several research efforts have been made to explore factors contributing to drivers' merging behavior. Marczak et al. (2013) concluded that the distance between the merging vehicle and the start of the acceleration lane, the gap between the lead and lag vehicles in the target lane, the difference in speed between the merging vehicle and the lag vehicle have significant effects on the merging behavior. Larger distance between the merging vehicle and the start of the acceleration lane, larger gap between the lead and lag vehicles in the target lane, and smaller speed difference will lead to a higher probability of merging. Sun et al. (2014) and Chu et al. (2017) considered more possible factors including the speed of merging vehicles, relative distance between merging vehicles and surrounding vehicles, and traffic conditions in the analysis of merging behavior. It was found that relative distance between merging vehicles and surrounding vehicles, congested traffic condition could have a negative effect on the probability of merging, while the speed of merging vehicles has a positive effect. In addition, Kondyli and Elefteriadou (2009) conducted a focus group method to explore the effects of drivers' characteristic on the freeway-ramp merging maneuver. Although several previous studies have investigated the affecting factors on the merging behavior, a comprehensive analysis of drivers' merging decisions by considering various possible factors such as driver-related variables, traffic conditions, and interactions between merging vehicles and surrounding vehicles are still missing. Also, the factors contributing to the mandatory-lane-change-related crash risk at merging areas need to be further studied.

In order to analyze the merging behavior and safety at the individual level, it is necessary to obtain accurate trajectories of all vehicles at the interchange merging area. With the rapid development of computer vision and image processing technology, video data has been widely used to collect vehicle trajectories. A traditional way to get the videos of the merging segment is setting a fixed camera on a high building or a high pole near the study segment. However, there are some limitations: (i) the required height is great while rare buildings are available for recording videos near the interchanges area; (ii) these videos are recorded at a tilt angle, which could cause more errors when processing the video data; (iii) the shooting range of the camera is restricted by the height of building or pole. Considering these limitations, an unmanned aerial vehicle (UAV) could be a better alternative to record video data for merging segments. UAVs can fly at a proper height to cover a large area flexibly with a considerably low cost without affecting drivers' behaviors (Khan et al., 2017). Many researches have used UAV for monitoring and analyzing traffic flow and safety (Kanistras et al., 2015; Kaufmann et al., 2018; Khan et al., 2018). Although the use of UAV in traffic studies is still at an early stage, it might play an important role in safety diagnosis and event detection in the future because of its mobility and flexibility.

In summary, this study aims to analyze drivers' mandatory-lane-change-related crash risk at the interchange merging area. To this end, a framework to investigate the mandatory-lane-change-related crash risk is proposed by incorporating the merging behavior with a safety measure. Then, a UAV video data processing method is introduced to obtain vehicles' trajectory data and other data of important factors (e.g., driving ability, merging speed, and the remaining distance to the end of acceleration lane). Factors having significant effects on drivers' merging behavior and safety will be identified. Finally, the distribution of mandatory-lane-change-related crash risk will be provided based on the results.

This paper is organized as follows. The following section gives the framework of the mandatory-lane-change-related crash risk considering merging behaviors. Next, the data collection and processing steps are presented. Section four presents the model results and discussions. The final section offers conclusions and suggestions for the future work.

## 3. Methodology

### 3.1. Drivers' merging behavior model

The merging process from an entrance ramp into the freeway lanes constitutes an important consideration of freeway and acceleration lane traffic conditions. Fig. 1 shows the typical geometric construction and merging process at interchange merging areas. There are two basic lanes relevant to the vehicles' merging process. One is the acceleration (auxiliary) lane, which is used for on-ramp vehicles to accelerate before merging with the through-traffic flow; the other is defined as the target lane adjacent to the acceleration lane that on-ramp vehicles will merge into. As shown in Fig. 1, four types of vehicles could be involved in the merging process: merging vehicle $m$ which is a vehicle travelling in the acceleration lane; lead merging vehicle $m$ -1 which is another merging vehicle in front of merging vehicle m; lead vehicle $n-1$ which is the lead vehicle relative to merging vehicle $m$ in the target lane; lag vehicle $n$ which is the lag vehicle relative to merging vehicle $m$ in the target lane.

The merging vehicles are allowed to merge into the freeway after they reach the soft nose (Fig. 1), and by that point drivers of merging vehicles could observe traffic condition of the target lane. The soft nose is defined as the beginning of the merging process. The merging decision point when the drivers decide to conduct a merging maneuver is not fixed and difficult to get through video data. Hence, an entire merging duration is considered in this study, which begins at the soft nose and ends at the point where a driver finishes a merging maneuver (i.e. merging vehicle fully enters the target lane). On-ramp drivers have to make merging decisions by synthesizing the surrounding roadway and traffic information after they enter the acceleration lane. Consequently, we assume drivers' merging behavior is a sequential decision process with two statuses: "complete a merging maneuver" if the merging vehicle fully enters the target lane and "not complete a merging maneuver" if not. Also, we consider the interactions between merging and neighboring vehicles as continuous actions across the whole merging process in this study.

For each time step, a merging driver needs to make a choice decision of merging or not, which is related to the driver's characteristics, traffic conditions, and the interactions with neighboring vehicles. Hence, a logistic regression model is employed to estimate the merging probability, which is used in identifying significant variables and investigating their impact. Note that a merging vehicle shares constant factors about driver's characteristics while the other factors about surrounding traffic conditions could be different during the whole merging process. Consequently, factors of two levels (i.e., situational and merging-driver-characteristic-related) need to be considered in this study. The situational factors can reflect the instantaneous traffic conditions such as vehicle speed, relative distance between merging vehicles and surrounding vehicles, and remaining distance to the end of the acceleration lane. These data were extracted at every time step during the whole merging process. Additionally, factors related to merging driver are characteristics such as drivers' confidence and driving ability which could affect drivers' merging decisions. Hence, this study employs a multilevel model which could properly estimate multilevel data by providing better model accuracy (Gelman, 2006). According to previous research (Weng et al., 2016; Sun et al., 2014), one second-based merging decision process is used in this study.

At any time step $t$, the merging driver $m'$ may either make a decision of "$y^t_{m'} = 1$" or "$y^t_{m'} = 0$" . Once the merging driver $m'$ makes a choice decision of "$y^t_{m'} = 1$", namely fully entering the through lane, the merging decision process ends at time $t + 1$. Hence, the sequential choice process of merging vehicle $m$ can be expressed by $(\underbrace{0\ldots0}_{t-1}, \underbrace{1}_{t})$. In addition, one issue needs more attention is that there might exist correlation between drivers' merging behaviors at different time steps. However, this study focuses on the probability of driver's merging decision given current situation at each time step. And this should be an independent process while there are correlations for the same driver. Furthermore, the driver-related level can explain parts of effect on one driver's different merging decisions during the entire merging duration from driver's aspects. Additionally, the use of random parameters below can also be a way to consider correlations for the same driver.

#### 3.1.1. Multilevel logistic regression model

For the situational level, the expected merging decision probability can be expressed by

$$logit(p^t_m) = \boldsymbol{\beta x^t_m} + d_m \quad (1)$$

Where $p^t_m$ is the probability of merging vehicle $m$ completing the merging maneuver at time $t$ ; $\boldsymbol{x^t_m}$ is a set of situational explanatory variables while $\boldsymbol{\beta}$ is a set of corresponding coefficients, $d_m$ is the merging-driver-characteristic-related effect, which could be estimated as follows:

$$d_m = \boldsymbol{\gamma w_m} \quad (2)$$

Where $\boldsymbol{w_m}$ is a set of explanatory variables in merging-driver-characteristic-related level and $\boldsymbol{\gamma}$ is a set of regression coefficients.

#### 3.1.2. Random parameters

While the multilevel logistic regression model could appropriately account for the data structure, the same variable may vary across

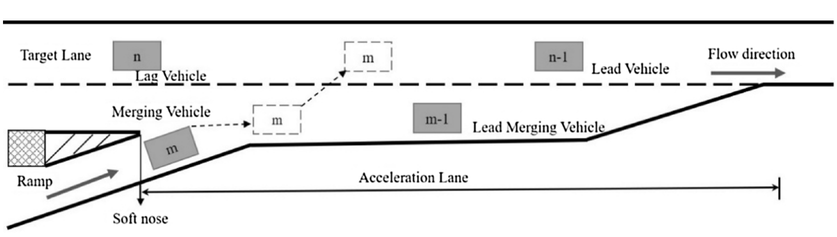


**Fig. 1.** Geometric construction and merging process at interchange merging areas.

different drivers due to unobserved heterogeneity. If the unobserved heterogeneity is ignored, the model would be misspecified and the estimated parameters could be biased and inefficient (Mannering et al., 2016). To address this issue, we use random parameters for the above multilevel logistic regression model (Anastasopoulos and Mannering, 2011; Barua et al., 2016; Cai et al., 2018a, 2018b; Russo et al., 2014). The random parameters can be expressed by

$$\beta_{ij} = \beta + \delta_{ij} \tag{3}$$

where subscript $i$ denotes each merging vehicle, and subscript $j$ indicates each observation for the merging vehicle at each time step during the entire merging duration, and $\beta$ is the mean estimated parameter across observations, $\delta_{ij}$ is randomly distributed terms which follows a normal distribution with mean zero. Since different merging drivers should have diverse perception for surrounding traffic conditions, there could be significant heterogeneity for situational variables observed for different drivers. Also, for the merging decisions at each time step of one driver, they may share the same unobserved heterogeneity, which means that panel data effects need to be considered. Hence, in this study, it was specified that the situational variables have random parameters that vary at the vehicle level, by defining the estimated explanatory as grouped random parameters $\beta_i$ for vehicle $i$. It can be expressed by:

$$\beta_i = \beta + \delta_i \tag{4}$$

where subscript $i$ denotes each merging vehicle, and $\beta$ is the mean estimated parameter across observations, and $\delta_i$ is the random distributed terms at the situational level.

### 3.1.3. Bayesian inference

As suggested in previous studies (Cai et al., 2017; Washington et al., 2005), Bayesian inference which can incorporate prior parameter information outperforms the traditional maximum likelihood estimation method. Also, Bayesian inference could provide full distribution of the parameters other than treating the coefficients of independent variables as fixed values. Hence, the multilevel logistic regression model was estimated in freeware WinBUGS using Markov Chain Monte Carlo (MCMC) simulation. In the absence of sufficient prior information, the priors for the parameters are set as non-informative with zero mean and a large variance, i.e., Normal (0, $10^6$). The non-informative approach has been widely used in the previous studies (Xu et al., 2014; Yuan and Abdel-Aty, 2018; Yuan et al., 2018; Wang et al., 2018). Parameters' convergence were evaluated by visual examination of the MCMC trace plots. The 90% Bayesian credible interval (BCI) is provided to examine the significance of variables. The Deviance Information Criteria (DIC) was used as a Bayesian measurement for the model performance comparisons. In addition to DIC, the AUC value, namely the area under Receiver Operating Characteristic (ROC) was also used to evaluate the random parameter multilevel logistic regression model, which is a better measure compared to sensitivity and specificity (Hosmer et al., 2013). A higher AUC value indicates a better discrimination for the merging versus non-merging maneuver.

## 3.2. Mandatory-lane-change-related crash risk

While a merging vehicle is in the acceleration lane, it needs to make a merge decision and complete the merging maneuver before reaching the end of the acceleration lane. If the lead merging vehicle is moving at a low speed, the merging vehicle needs to either change lane or decrease speed to avoid a collision. Otherwise, a rear-end crash may occur. If the merging vehicle enters the target lane, there is also a probability of crash between the merging vehicle and the lead/lag vehicle in the target lane. The crash in the target lane might include rear-end or sideswipe crash. For simplification, we use lane change crash risk to represent the crash risk in the target lane. Hence, the mandatory-lane-change-related crash risk of merging vehicle consists of two parts: rear-end crash risk in the acceleration lane and lane change crash risk in the target lane.

Time to collision (TTC) is a widely used safety surrogate measure in estimating the individual vehicle crash risk (Cai et al., 2018a, 2018b; Oh and Kim, 2010). TTC is defined as 'the time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained (Hydén, 1996). The TTC between the merging vehicle and lead merging vehicle in the acceleration lane can be calculated by:

$$TTC_m^{m-1}(t) = \frac{d_m^{m-1}(t)}{v_m(t) - v_{m-1}(t)},\ if\ v_m(t) > v_{m-1}(t) \tag{5}$$

Where $TTC_m^{m-1}(t)$ is the TTC value between the merging vehicle $m$ and the lead merging vehicle $m-1$, $d_m^{m-1}(t)$ is the lead gap between merging vehicle $m$ and lead merging vehicle $m-1$, $v_m(t)$ is the speed of merging vehicle $m$, $v_{m-1}(t)$ is the speed of the lead merging vehicle $m-1$ in the acceleration lane.

The TTC between the merging vehicle and lead/lag vehicle in the target lane can be calculated by

$$TTC_m^{n-1}(t) = \frac{d_m^{n-1}(t)}{v_m(t) - v_{n-1}(t)},\ if\ v_m(t) > v_{n-1}(t) \tag{6}$$

$$TTC_n^{m}(t) = \frac{d_n^{m}(t)}{v_n(t) - v_m(t)},\ if\ v_n(t) > v_m(t) \tag{7}$$

where $TTC_m^{n-1}(t)$is the TTC value between the merging vehicle $m$ and the lead vehicle $n-1$ in the target lane, $TTC_n^m(t)$is the TTC value between the lag vehicle $n$ in the target lane and the merging vehicle $m$, $d_m^{n-1}(t)$ is the lead gap between the lead vehicle $n-1$ in the target lane and the merging vehicle $m$, $d_n^m(t)$ is the lag gap between the lag vehicle $n$ in the target lane and the merging vehicle $m$ ; $v_{n-1}(t)$ is the speed of lead vehicle $n-1$ in the target lane, $v_n(t)$ is the speed of lag vehicle $n$ in the target lane.

Note that a TTC value could reflect the potential crash risk. A smaller TTC represents a higher probability for the merging vehicle to have a crash with another vehicle. However, a drawback of using TTC as a crash risk index is that it is not consistent with the change trends of crash risk (Chu et al., 2017). In order to overcome this drawback, some attempts have been made to use an inverse TTC (Balas and Balas, 2006; Kiefer et al., 2005) and exponential decay function (Oh and Kim, 2010) to evaluate the crash risk. In this study, TTC value could be equal to zero if the merging vehicle takes the choice of "complete merging" when it is parallel to a vehicle on the target lane (Fig. 2). Hence, an exponential decay function is used to describe the relationship between the TTC and the crash risk:

$$CR = e^{\frac{-TTC}{c}} \tag{8}$$

Where $CR$ is the TTC-based crash risk and parameter $c$ indicates the number of crashes of the studied road segment (Oh and Kim, 2010). For example, with the same value of TTC, a larger $c$ value indicates a higher crash level for the road segment. For simplification, a $c$ value of 1 will be used in this study. Also, the $c$ value could be specified in the future if more data would become available.

As mentioned above, if a merging vehicle takes a merging maneuver, it may have collisions with the leading and lag vehicles in the

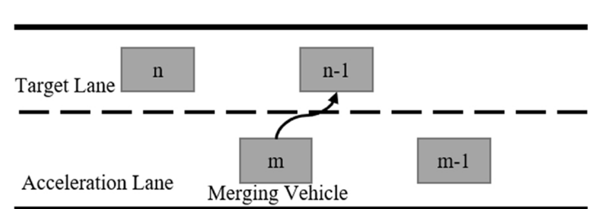


**Fig. 2.** The case that TTC = 0.

target lane. Otherwise, it may have a collision with the lead vehicle in the acceleration lane. Then the lane change crash risk of the merging vehicle in the target lane can be calculated by the probability of merging and the crash risk between leading and lag vehicles:

$$CR_m^t(target) = p_m^t \times (CR_{m,n-1}^t + CR_{m,n}^t) \quad (9)$$

where $CR_m^t(target)$ is the lane change crash risk of merging vehicle $m$ at time $t$ in the target lane, $p_m^t$ is the probability of merging vehicle $m$ completing the merging maneuver at time $t$, $CR_{m,n-1}^t$ is the lane change crash risk between the merging vehicle $m$ and the lead vehicle $n-1$ in the target lane at time $t$, $CR_{m,n}^t$ is the lane change crash risk between the merging vehicle $m$ and the lag vehicle $n$ in the target lane at time $t$.

Similarly, the rear-end crash risk of the merging vehicle in the acceleration lane can be calculated by using the probability of not merging and the rear-end crash risk between lead and lag vehicles:

$$Np_m^t = 1 - p_m^t \quad (10)$$

$$CR_m^t(accelerate) = Np_m^t \times CR_{m,m-1}^t \quad (11)$$

where $Np_m^t$ is the probability of merging vehicle $m$ not completing the merging maneuver at time $t$, $CR_m^t(accelerate)$ is the rear-end crash risk of merging vehicle $m$ at time $t$ in the acceleration lane, $CR_{m,m-1}^t$ is the rear-end crash risk between the merging vehicle $m$ and the lead vehicle $m-1$ in the acceleration lane at time $t$.

Hence, the total crash risk of merging vehicle can be calculated as the sum of the crash risk in the target lane and the acceleration lane:

$$CR_m^t(total) = CR_m^t(target) + CR_m^t(accelerate) \quad (12)$$

where $CR_m^t(total)$ is the total crash risk of merging vehicle $m$ involving in a crash risk at time $t$.

### 3.3. Analysis framework

The total mandatory-lane-change-related crash risk of merging vehicle includes two parts: the lane change crash risk with the lead/lag vehicle in the target lane, and the rear-end crash risk with the lead merging vehicle in the acceleration lane. Specifically, the lane change crash risk with the lead/lag vehicle in the target lane is determined by the probability of merging and TTC-based crash risk. Similarly, the rear-end crash risk with the lead merging vehicle in the acceleration lane can be calculated by the probability of not merging and TTC-based crash risk. Hence, a framework can be extracted to estimate the total crash risk for merging vehicles at interchange merging area by incorporating the merging behaviors with a safety measure (Fig. 3).

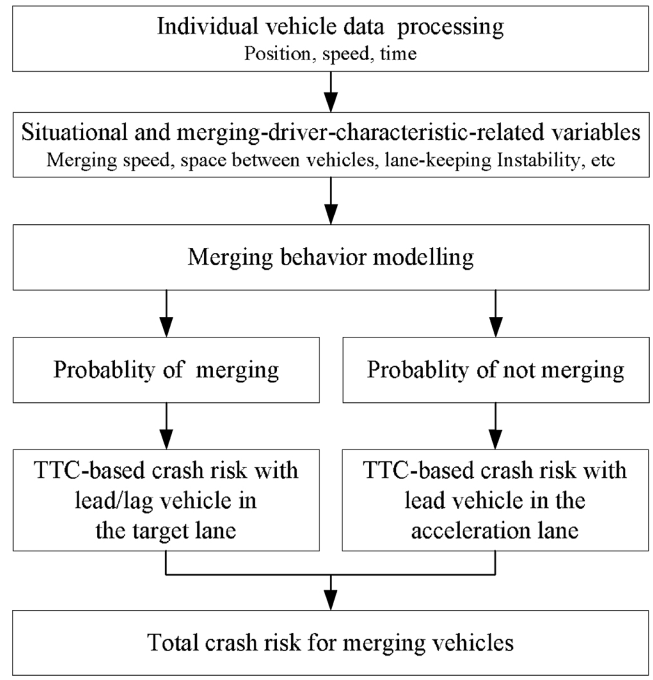


**Fig. 3.** The analysis framework of the mandatory-lane-change-related crash risk.

## 4. Data

To illustrate the analysis framework of the mandatory-lane-change-related crash risk proposed in Section 3, a field study was conducted at the merging area of Maqun Interchange in Nanjing, China. It has one acceleration lane and four lanes that change to three lanes at the end of the acceleration lane. The length of the acceleration lane is 220 m. The video data has been collected using the DJI Inspire 1, a small-scale quadcopter camera drone. UAV photography allows shooting videos under some requirements, including the wind force below grade 4, sunny weather, good light, and no electromagnetic interference, which could output stable video pictures at a vertical angle. The aerial video recording has been conducted at a height of 200 m during the peak and non-peak periods. The camera range extended approximately 80 m upstream and 100 m downstream of the acceleration lane with a total length of 410 m, which could guarantee to catch the vehicles' movements and interactions in the target and acceleration lanes. The vehicle trajectory data were extracted from the videos using an open video processing software Tracker, which can provide the position of vehicles in each video frame (60fps). As shown in Fig. 4, the red plots are the trajectories of merging vehicles and the black plots are the trajectories of vehicles from the mainline. When processing the video data, the length of lane marking was considered as a reference to calibrate the distance, so the error caused by the projection of the videos could be ignored.

Since the vehicle speed is calculated by dividing the distance by the time of two contiguous frames, little error of vehicle position might have a significant effect on speed value. For example, if a measurement error is 0.1 m, the speed error is:1 pixel/frame ≅ 0. 1 m/(1/60 s) = 6 m/s. To avoid this speed error, a moving average (MA) method is used to help smooth out vehicle positions and yield reasonable vehicle's speed without the noise. As shown in Fig. 5, a measurement point at time $t$ is considered for the MA procedure. All measurements are performed with MA within a time interval $t - 0.5T \le t \le t + 0.5T$, where $T$ is the selected time duration for conducting MA process. An example of MA with $T = 2s$ is shown in Fig. 5a, in which the position at time $t$ is calculated as the average of the former 60 points and the latter 60 points. In this example, 120 frames are used to conduct the MA procedure. As shown in Fig. 5b, the speed values obtained without MA have a big deviation. Hence, the result of MA has a significant impact on the speed value. In order to investigate the effects of space and time on the averaged speed, the MA procedure with a time duration $T$ and a sampling rate $F$ was performed. Time duration $T$ is the time interval to conduct the MA procedure and sampling rate $F$ is the number of position points selected to calculate the speed value. Fig. 5c-g show the different results of the MA procedure with different time duration $T$ and sampling rate $F$. It can be concluded that higher MA time duration and lower sampling rate would provide smoother lines. Finally, a time duration $T = 2s$ and a sampling rate $F = 4Hz$ were chosen because in this case we can remove most of the jitters and avoid loss of information due to too much smoothing.

The merging decision that a driver must make is highly affected by the interaction with surrounding vehicles and the drivers' driving ability. Hence, acceleration lane-related variables, target lane-related variables, and merging vehicle-related variables were extracted from each set of collected trajectory data. Fig. 6 and Table 1 show the definition and descriptive statistics of key variables, respectively. In this study, two types of vehicles are considered, 0 for the passenger car and 1 for heavy vehicles (i.e., bus, truck, and semi-trailer). It should be

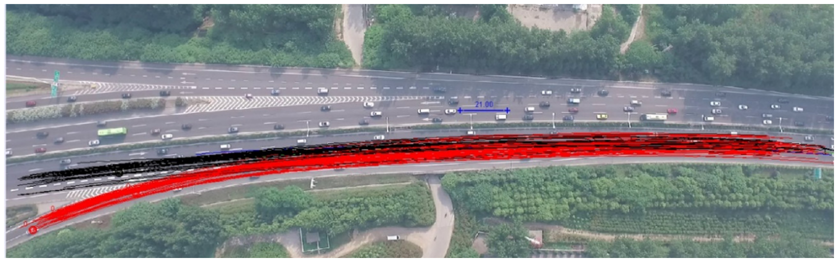

**Fig. 4.** Vehicle trajectories of merging area at Maqun Interchange.

pointed out that the type of lead vehicle in the target lane are divided into three categories according to the videotape: passenger car, heavy vehicles, and no lead vehicle. And it was converted to dummy variable in the model. Note that during the merging process, merging drivers could only observe the driving status of lag vehicle through the side mirror. If a lag vehicle in the target lane is far from the merging vehicle, the lag vehicle should have little impact on the merging maneuver since the driver of the merging vehicle could not observe the lag vehicle. According to the previous study (Wu et al., 2013), a rear blind spot length of 20 m is used to determine if there is a lag vehicle existing in the drivers' observation zone. Given that run-off-road crashes frequently occur on ramps (McCartt et al., 2004), which might be relative to improper lane-keeping, a variable representing drivers' lane-keeping ability is extracted and assumed to impact the merging maneuver. If the merging vehicles move across the right boundaries of ramp lane, we define the drivers' lane-keeping ability as unstable; if not, it is stable. Besides, another variable related to driving ability was extracted. If the merging vehicles continue changing lanes after they complete the merging maneuver, the drivers should be more confident with their driving ability and traffic condition. Hence, if drivers make a continuous lane changing maneuver, the drivers' lane change confidence is defined as strong; if not, it is weak.

## 5. Results and discussion

### 5.1. Merging behavior model

Bayesian multilevel random parameters logistic regression was used to model the merging behavior. In order to avoid the multicollinearity problem, variables were checked for possible high correlations. If the correlation coefficient of two variables was higher than 0.4, only the variable providing a lower DIC was kept.

As previously mentioned, earlier studies have found that the merging behavior was significantly affected by the traffic conditions, relative distance, the speed of the merging vehicle and its surrounding vehicles. Key variables of acceleration lane, target lane, merging vehicle, and merging driver characteristics were considered as the candidate explanatory variables for modelling. The estimated explanatory variable parameters and related statistical analysis results of the merging behavior model are presented in Table 2. The area under the Receiver Operating Characteristic (ROC) were used to measure the model performance.

Based on the estimation results of the model, eleven variables were found to be significantly associated with the drivers' merging decision. The negative coefficient (-1.05) of Ln_Volume_AL indicates that higher volume in the acceleration lane tends to decrease the probability of merging decision. With a high volume, merging vehicles do not have

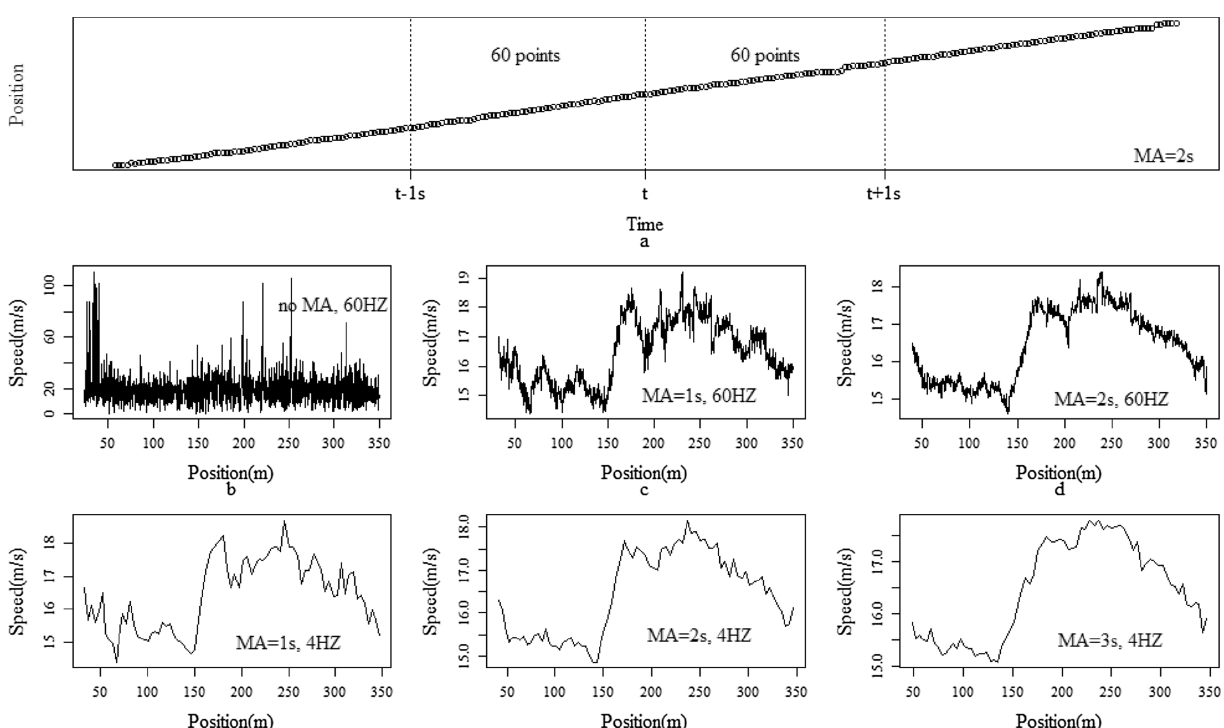


**Fig. 5.** Explanation of the procedure of moving average(MA) (a) position plots of a single vehicle trajectory and moving average time duration. (b–g) speed plots of a single vehicle trajectory derived with a moving average(MA) in which different values of MA time duration $T$ and different sampling rates $F$ have been applied.

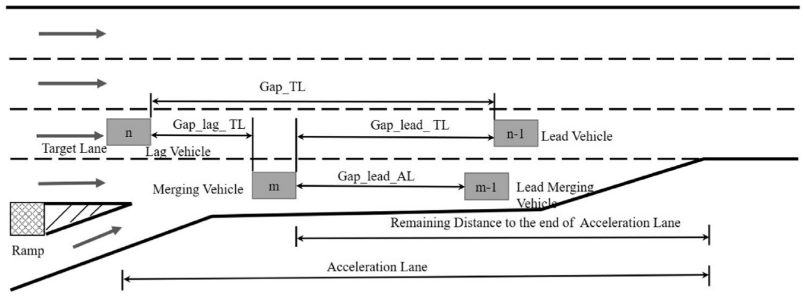


**Fig. 6.** Definition of key variables.

enough space to speed up in a congested acceleration lane and also have no accepted gap for them to merge, which force them continue car-following maneuver to get ready for merging. The preceding gap between the merging vehicle and the lead merging vehicle in the acceleration lane has a negative effect on the merging decision. It may be because the merging vehicle with a large gap with the lead vehicle in the acceleration lane should be more likely to speed up to get prepared to merge into the target lane. As expected, the total gap between the lead vehicle and lag vehicle in the target lane is positively correlated with the merging decision, which implies that the merging driver will select to merge into the target lane if there is an enough gap between the lead vehicle and lag vehicle in the target lane. In addition, the vehicle type of the lead vehicle in the target lane also has a significant effect on the drivers' merging behavior. There is a high possibility that the merging vehicle will complete the merging maneuver if there is no lead vehicle in the target lane. However, the merging vehicle is more likely to stay in the acceleration lane if the lead vehicle in the target lane is a heavy vehicle.

The speed of merging vehicles and surrounding vehicles are also significant variables which greatly affect the drivers' merging behavior. Specially, a positive correlation was found between the speed of lead vehicles in the target lane and the merging behavior. This could be explained that the merging driver may overestimate the average speed in the target lane because of the high speed of lead vehicles, thus drivers would take more time to speed up to achieve a higher speed level. On the contrary, the speed of lag vehicles in drivers' observation zone in the target lane is negatively correlated with the merging behavior. The finding is reasonable since the merging drivers will not choose to merge if they find that a lag vehicle is approaching with a high speed. Meanwhile, the speed of merging vehicles was found to have a positive effect on merging behavior, which means that drivers with larger merging speed will complete the merging maneuver as soon as possible. Note that the speed of merging vehicles and the speed of lag vehicles in the target lane have significant standard deviations of the parameter density function in the model, which suggests that the two variables have unobserved heterogeneity across vehicles.

Furthermore, the remaining distance from the merging vehicle to the end of acceleration lane was found to be negatively correlated with the merging decision likelihood since the merging drivers should not be in hurry if a large distance remains. According to the results, two driver-characteristic-related variables are significant in the model, i.e., lane-keeping instability and lane change confidence. Lane-keeping instability has a negative effect on the merging decision, which implies that the merging drivers who have unstable lane-keeping ability need

**Table 1**
Descriptive statistics for variable collected from the merging area survey.

| Variables | Description | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|---|
| **Situational variables** | | | | | |
| *Acceleration Lane* | | | | | |
| Volume_AL | Volume of vehicles (Vehicles/second) | 5.70 | 2.69 | 1.00 | 15.00 |
| Blead_AL | Existence of a lead merging vehicle (yes = 1, no = 0) | 0.72 | 0.45 | 0 | 1 |
| Type_lead_AL | The type of lead merging vehicle | 0.05 | 0.23 | 0 | 1 |
| Gap_lead_AL | The preceding gap between the merging vehicle and the lead merging vehicle(m) | 46.80 | 41.99 | 2.00 | 215.10 |
| Speed_lead_AL | The speed of lead merging vehicle(m/s) | 12.90 | 8.27 | 0.00 | 26.81 |
| Dspeed_lead_AL | The speed difference between merging vehicle and lead merging vehicle(m/s) | 4.92 | 8.68 | −9.57 | 26.65 |
| *Target Lane* | | | | | |
| K_TL | The density of target lane(vehicles/m) | 20.97 | 8.26 | 3.28 | 55.74 |
| Gap_TL | The total gap between the lead vehicle and lag vehicle in the target lane(m) | 91.02 | 57.54 | 8.40 | 340.00 |
| TypeH_lead_TL | Lead vehicle in the target lane is heavy vehicle | 0.24 | 0.43 | 0 | 1 |
| TypeN_lead_TL | There is no lead vehicle in the target lane | 0.01 | 0.05 | 0 | 1 |
| Speed_lead_TL | The speed of lead vehicle in target lane(m/s) | 19.35 | 3.40 | 12.29 | 34.60 |
| Dspeed_lead_TL | The speed difference between merging vehicle and lead vehicle in the target lane (m/s) | −1.52 | 3.64 | −11.23 | 7.66 |
| Gap_lead_TL | The lead gap between merging vehicle and lead vehicle in the target lane(m) | 43.03 | 42.40 | 0.00 | 200.00 |
| Speed_lag_TL | The speed of lag vehicle in the target lane | 16.89 | 7.14 | 0.00 | 31.29 |
| Dspeed_lag_TL | The speed difference between lag vehicle in the target lane and merging vehicle (m/s) | −0.94 | 7.34 | −26.65 | 13.22 |
| Blag_TL | Existence of a lag vehicle in drivers' observation zone (yes = 1, no = 0) | 0.30 | 0.46 | 0 | 1 |
| Gap_lag_TL | The lag gap between lag vehicle in the target lane and merging vehicle(m) | 45.52 | 44.93 | 0.00 | 190.00 |
| *Merging Vehicle* | | | | | |
| Speed_M | The speed of merging vehicle(m/s) | 17.82 | 2.13 | 11.20 | 26.65 |
| Acce_M | The acceleration of merging vehicle(m/s2) | 1.93 | 0.94 | 0.00 | 5.51 |
| Type_M | The type of merging vehicle | 0.06 | 0.24 | 0.00 | 1.00 |
| TimeElaspe | Time elapsed for the merging vehicle after the merging maneuver is triggered(s) | 5.23 | 3.54 | 0.00 | 19.42 |
| TimeDuration | The total time of merging process(s) | 8.19 | 3.74 | 2.10 | 19.42 |
| Distance_AL | The remaining distance from the merging vehicle to the end of acceleration lane(m) | 126.88 | 60.50 | 0.00 | 216.80 |
| **Merging driver characteristics** | | | | | |
| LanekeepingInstability | Lane-keeping ability (unstable = 1, stable = 0) | 0.41 | 0.49 | 0 | 1 |
| LaneChangeConfidence | Lane change confidence (strong = 1, weak = 0) | 0.12 | 0.32 | 0 | 1 |

**Table 2**
Modeling results of drivers' merging behavior.

| Variable | Description | Mean | Standard Error | 5% | 95% |
|---|---|---|---|---|---|
| Intercept | | 8.70** | 6.37 | 1.05 | 21.66 |
| **Situational variables** | | | | | |
| Ln_Volume_AL | Logarithmic transformation of volume of vehicles in acceleration lane | −1.05** | 0.24 | −1.48 | −0.71 |
| Gap_lead_AL | The preceding gap between the merging vehicle and the lead merging vehicle in the acceleration lane | −0.02** | < 0.01 | −0.03 | −0.02 |
| Gap_TL | The total gap between the lead vehicle and lag vehicle in the target lane | 0.01* | < 0.01 | < 0.01 | < 0.01 |
| TypeH_lead_TL | Lead vehicle in the target lane is heavy vehicle | −0.91** | 0.27 | −1.38 | −0.48 |
| TypeN_lead_TL | There is no lead vehicle in the target lane | 4.30** | 1.70 | 4.26 | 7.26 |
| Speed_lead_TL | The speed of lead vehicle in target lane | −0.11** | 0.04 | −0.17 | −0.04 |
| Speed_lag_TL* Blag_TL | The speed of lag vehicle in drivers' observation zone in the target lane | −0.04** | 0.01 | −0.06 | −0.02 |
| Standard deviation of parameter distribution | | 0.03** | < 0.01 | 0.02 | 0.05 |
| Speed_M | The speed of merging vehicle | 0.11** | 0.06 | 0.02 | 0.21 |
| Standard deviation of parameter distribution | | 0.05** | 0.02 | 0.02 | 0.08 |
| Distance_AL | The remaining distance from the merging vehicle to the end of acceleration lane | −0.03** | < 0.01 | −0.03 | −0.02 |
| **Merging driver characteristics** | | | | | |
| Intercept | | −5.49 | 6.20 | −18.28 | 2.42 |
| LaneKeepingInstability | Drivers' lane-keeping ability (unstable = 1, stable = 0) | −0.87** | 0.31 | −1.39 | −0.43 |
| LaneChangeConfidence | Drivers' lane change confidence (strong = 1, weak = 0) | 2.02** | 0.37 | 1.46 | 2.68 |
| *AUC* | | 0.85 | | | |

*Significant at the 90% confidence level; **Significant at the 95% confidence level.

more time to complete the merging maneuver. The positive coefficient of lane change confidence indicates that the merging drivers who are confident in changing lanes have a high probability of merging due to a quick judgement of surrounding conditions and a short set-up time.

Note that the variable 'time duration of merging process' was considered to control the possible effect on the model, which might result from the sample size of different vehicles. The time duration of merging process was found to have a negative effect on the merging maneuver. One possible reason for this result might be that a longer time duration which indicates a longer exposure time for being affected by surrounding vehicles and leading to a longer delay. However, this variable is not inputted into the model due to the multicollinearity problem.

### *5.2. Mandatory-lane-change-related crash risk based on TTC and merging behavior model*

At each time step, the possibility for the merging vehicle to take the merging maneuver could be calculated by using the estimated merging behavior model in Section 5.1. Then, the crash risk for the merging vehicle for each time step can be calculated based on TTC according to Eqs. (5)–(12). Note that only TTCs which are positive and less than 20 s will be considered in this study. The negative TTC value indicates that there is no crash risk since the speed of the following vehicle is less than the speed of the lead vehicle. Meanwhile, the TTCs over 20 s suggest very safe conditions. We will investigate the effects of factors on the mandatory-lane-change-related crash risk in this section.

#### *5.2.1. Effects of drivers' driving ability on mandatory-lane-change-relatedcrash risk*

Fig. 7 graphically shows the relationship between the overall crash risk and the drivers' driving ability. As expected, it is more likely for drivers who have unstable lane-keeping ability to suffer a collision. One possible reason for this result might be that drivers with unstable lane-keeping ability, namely moving across the right boundaries of ramp lane, will misestimate the surrounding traffic conditions due to a limited vision. Besides, these drivers might be weak in lateral movement during lane change. Similarly, the possibility of crash risk is higher when drivers have weak lane change confidence. There might be two reasons: the traffic condition in the target lane and adjacent freeway lanes should be good to allow merging drivers to make a continuous lane change maneuver; drivers with strong lane change confidence might get a more accurate estimation of the surrounding traffic condition.

#### *5.2.2. Effects of merging vehicle speed on mandatory-lane-change-related crash risk*

Fig. 8 presents the relationship between the speed of merging vehicle and mandatory-lane-change-related crash risk. It is found that there is no monotonic relationship between the merging vehicle speed and the crash risk. Specifically, the crash risk is high when the speed of the merging vehicle is either very low or very high. One possible reason for the high mandatory-lane-change-related crash risk at a low travelling speed might be the fact that heavy vehicles usually have a low speed at the beginning of the acceleration lane, which is substantially different from the surrounding vehicles. Furthermore, if the merging vehicles make a merging maneuver at a low speed, it is more likely for them to collide with vehicles in the target lane. However, a merging vehicle with a very high speed will increase the crash risk with the lead merging vehicle. According to the figure, a moderate merging speed ranging from 13.5 m/s to 26 m/s is suggested to make a merging decision because of the relatively low crash risk.

#### *5.2.3. Effects of remaining distance to the end of acceleration lane on mandatory-lane-change-related crash risk*

Fig. 9 shows the impacts of the remaining distance to the end of the acceleration lane to complete a merging maneuver on the rear-end crash risk in the acceleration lane. From the figure, a negative relationship could be found between the remaining distance to the end of the acceleration lane and the crash risk, which follows a logarithmic pattern. It might be explained that the merging vehicle would become more aggressive while they are approaching the end of the acceleration lane. For some vehicles, the crash risk is also high at the beginning of the acceleration lane. After checking the data, a relative high speed was found for these vehicles, which might be explained in the fact that the likelihood of rear-end crash risk is high when a merging vehicle has larger speed compared with the lead merging vehicle. Similarly, the crash risk in the target lane also has an exponential relationship with the remaining distance to the end of the acceleration lane (Fig. 10). When the merging vehicles are approaching the end of the acceleration lane, they would choose to merge even there exist high crash risks with the vehicles in the target lane.

To further explore the distribution of high crash risk point at the beginning of the acceleration lane, the total crash risk at the merging time were selected to be analyzed (Fig. 11). The nonlinear regression with the exponential function was conducted to explore the detailed relationship between the remaining distance and the total crash risk of completing the merging maneuver. And a midpoint of the acceleration

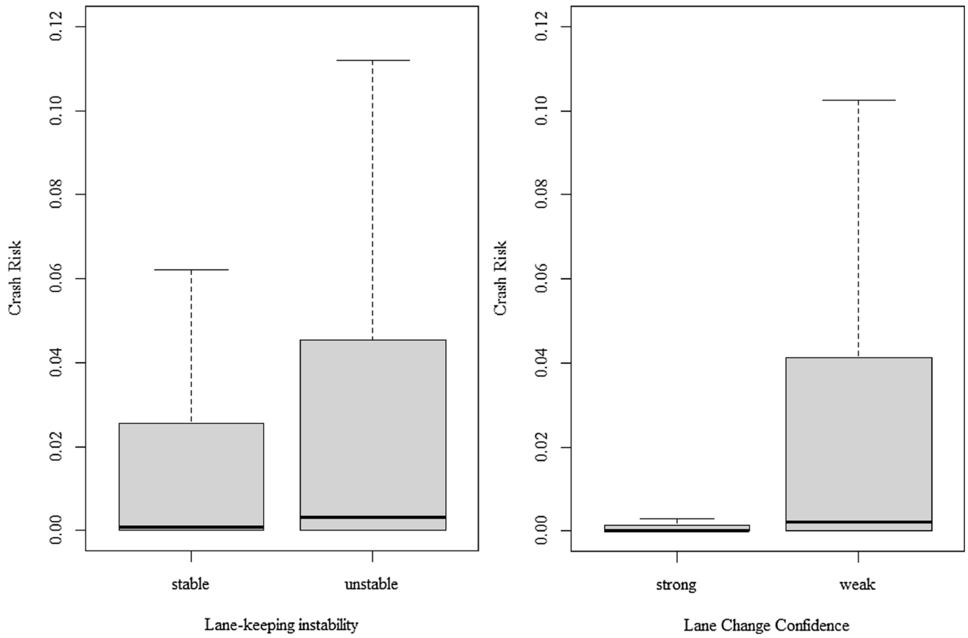


**Fig. 7.** Effects of drivers' driving ability on the mandatory-lane-change-related crash risk.

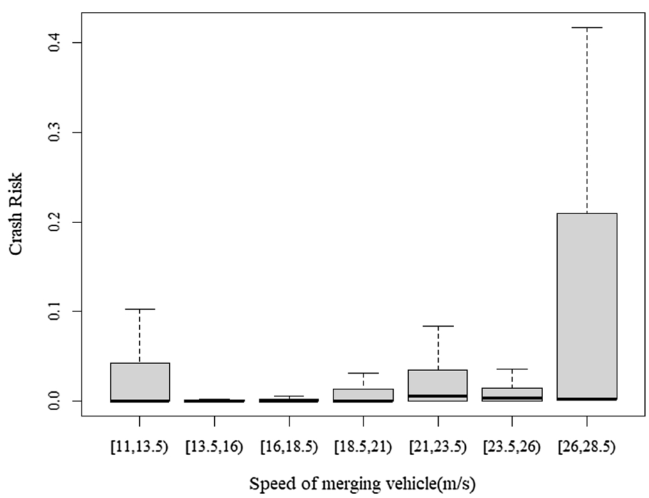


**Fig. 8.** Relationship between the speed of merging vehicle and the crash risk.

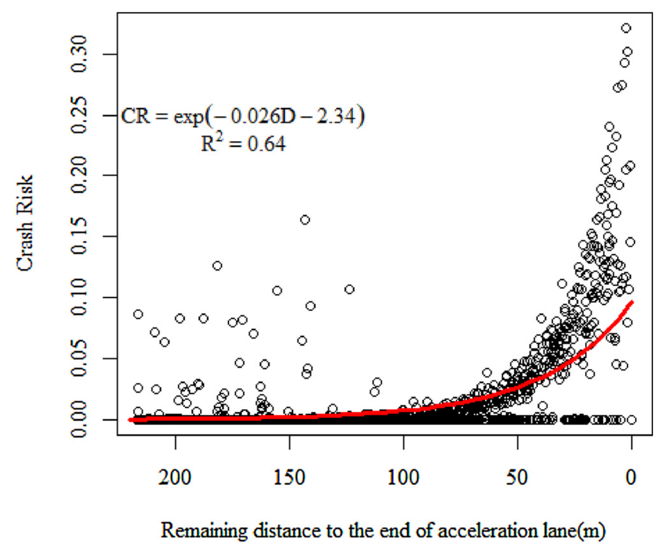


**Fig. 9.** Crash risk in the acceleration lane.

lane 110 m was selected to divide the model.

The equation suggests that the distance has a negative relation with the crash risk before vehicles pass the midpoint of the acceleration lane, which means that it is dangerous if the driver merges too early. Hence, a white solid line should be used to prevent drivers to merge at the beginning of the acceleration lane. On the other hand, the distance is positively associated with the crash risk after vehicle crosses the midpoint. When the residual distance gets limited, drivers need to take an urgent and mandatory merging maneuver, resulting in a higher crash risk.

## 6. Conclusions

This study sought to analyze the mandatory-lane-change-related crash risk during the entire merging implementation period at the interchange merging area. A new framework to explore the mandatory-lane-change-related crash risk by incorporating the merging behavior and a safety measure was proposed. To consider the merging behavior, a multilevel random parameters logistic regression model was developed to determine the probability that a merging vehicle completes the merging maneuver by analyzing key variables produced from a vehicle trajectory data set. Then, a method was suggested to compute the crash risk between the merging vehicle and its surrounding vehicles by incorporating the estimated merging behavior model with a safety measure (i.e., time-to-collision (TTC)). Based on the estimated mandatory-lane-change-related crash risk, the effects of drivers' driving ability, merging speed, and remaining distance to the end of the acceleration lane on the crash risk were examined.

For the merging behavior, the effects of driving ability, traffic conditions and the interactions between merging vehicles and surrounding vehicles were fully considered. The results showed that there is a high probability of completing a merging maneuver under one of the following situations:(i) the merging vehicle accelerates to a relative high speed, which is not too much different from the speed of vehicles in the target lane; (ii) the space between the lead vehicle and lag vehicle in the target lane is adequate for merging vehicle; (iii) the merging driver has a strong lane change confidence leading to an accurate estimation of the surrounding vehicles' speeds. However, the merging

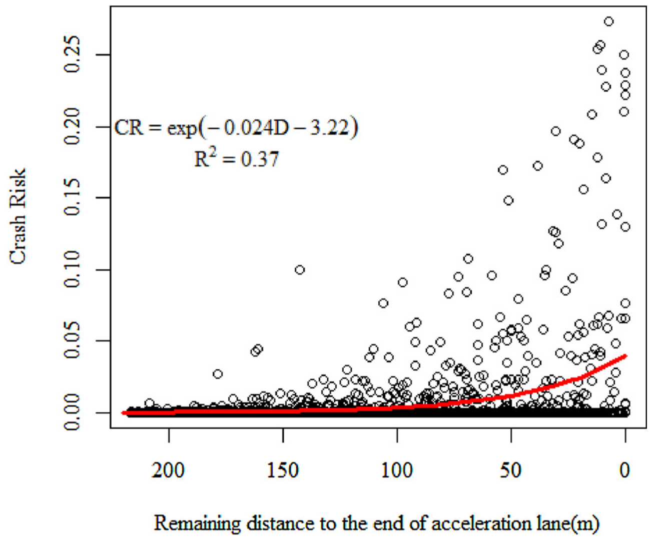


**Fig. 10.** Crash risk in the target lane.

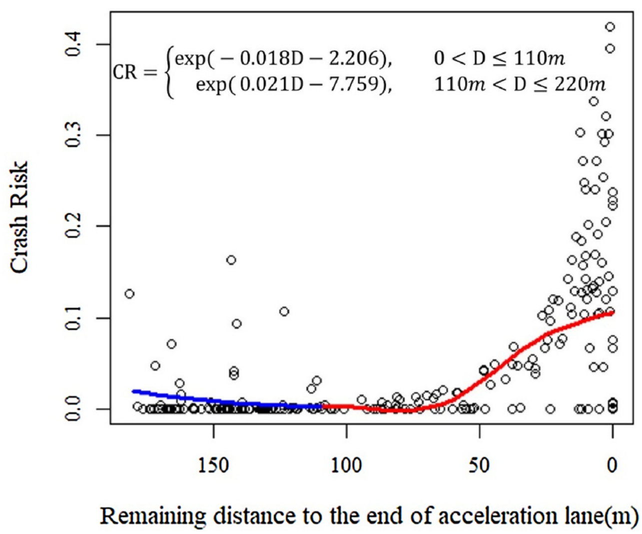


**Fig. 11.** Crash risk at the merging time.

driver prefers to delay the merging behavior when he/she does not achieve an adequate merging speed, which occurs in cases that there is a large volume in the acceleration lane and/or the speed of lead vehicle in the target lane is high. In addition, it is less likely to complete a merging maneuver when the lead vehicle in the target lane is a truck. It was also found that the likelihood of completing a merging maneuver decreases when drivers' lane-keeping ability is unstable.

The mandatory-lane-change-related crash risk results showed that it is highly affected by the driving ability. There will be high crash risk when the drivers' lane-keeping ability is unstable, as well as the lane change confidence is weak. Furthermore, the crash risk is relatively larger when the merging vehicle travels at a very high or very low speed, compared with travelling at an adequate speed. Another important finding was that the crash risk increases with the merging vehicle approaching the end of the acceleration lane and being forced to merge. Additionally, it was also found that the beginning of the acceleration lane is also a high crash risk area. Some helpful suggestions to reduce the mandatory-lane-change-related crash risk at the merging area can be designed according to the results of this study. For instance, the speed limit could be used to prevent on-ramp drivers completing a merging maneuver when they travel at a very low or very high speed. Additionally, a lane change ban mark (white solid line) could be used to prohibit the very early merging behavior. Also, the results could be used to better design connected vehicles to advise the driver of the most appropriate window to change lane or adjust speed, or advise a vehicle in the target lane to reduce speed to allow a gap for a merging vehicle, etc.

This study is not without any limitation. The merging behavior model was developed only based on data from one interchange area due to the difficulty of collecting and processing the data. In the future, collecting data from different interchanges to analyze the merging behavior might be worthwhile. In addition, some influencing factors that might also affect the crash risks are not considered, such as the geometry design and speed limit. Future studies could be conducted to develop a more generalized model by taking into account these factors. Another limitation of this study is that there might exist endogeneity in the model because of the correlations of the merging decisions of the same driver and the presence of lag variables. More effort could be conducted to explore the conditional independence of merging behaviors at different time periods in model development. The joint density which considers the cumulative probability of merging decisions will be investigated in the future study. Additionally, time series algorithms can be used to describe complex relationships between merging behaviors and larger data sample would need to be collected for model development.

## Acknowledgements

The study was funded by the Fundamental Research Funds for the Central Universities and Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYLX16_0274), and China's National Science and Technology Plan of Action for Traffic safety (2014BAG01B01), the National Natural Science Foundation of China (No. 71871059). The authors acknowledge the assistance provided by the graduate research assistants Zhanji Zheng and Fulin Chen, at the School of Transportation, Southeast University, in field data collection. Part of the research was conducted at the University of Central Florida where the first author spent a year as a visiting student funded by China Scholarship Council.

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