Examining traffic conflicts of up stream toll plaza area using vehicles' trajectory data☆

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ABSTRACT

Despite the recognized benefits of electronic toll collection (ETC) system as an important part of toll plaza area, the mixed traffic of electronic toll collection (ETC) vehicles and manual toll collection (MTC) vehicles in the toll plaza diverging area are considered risky to vehicles, in which complex diverging and crossing behavior of vehicles would increase the collision risks. Therefore, it is vitally important to investigate the vehicle collision risk in the up stream toll plaza area. Video data are collected from a typical toll plaza in Nanjing, China, and vehicle trajectory data are extracted using an automated analysis system based on OpenCV. An extended Time-To-Collision (TTC) is proposed to evaluate the vehicle collision risk. Subsequently, the different effects on vehicle collision risk of vehicles with different toll collection types, target lanes and locations are compared. Furthermore, the random parameters logistic model is developed to investigate the effects of explanatory factors on the collision risk of vehicles diverging or adjusting their lane position. The results suggested that the MTC vehicles have the highest collision risk in the toll plaza diverging area and there are significant different effects on collision risk among vehicles with different target toll collection lanes. Further, more dangerous situations could be found for a vehicle if it is closer to the toll collection lanes and surrounded by heavy traffic. It is also confirmed that mixed traffic with MTC and ETC vehicles could increase the crash risk in the toll plaza diverging area. It is expected that the findings could help engineers and operators select the appropriate engineering and traffic control solutions to enhance the safety at the toll plaza diverging area.

1. Introduction

Toll road has been extensively utilized to provide more convenient and efficient travel around the world. In the United States, such as Florida, toll road miles have almost doubled in the past decade (FDOT, 2014). In China, toll road kilometers increased to 171,100 km at the end of 2016, due to the traffic policy, approximately 95% of highways are tolled (Ministry Of Transport China, C., 2017). Although it can offer a high level of service and well-maintained roadways, traditional toll facilities may pose high risks for drivers, especially in the vicinity of the tollbooths.

There are 1575 toll plazas in China, in which mainline highway toll plazas account for 743 (Gao De, 2016). The toll collection lanes in toll plazas have two types, i.e. manual toll collection (MTC) lane and electronic toll collection (ETC) lane. Vehicles passing through MTC lanes (MTC vehicles) need to completely stop at the tollbooths, while vehicles passing via ETC lanes (ETC vehicles) just need to slow down and can be automatically charged by their ETC tags. Compared to MTC lanes, the ETC lanes can improve traffic capacity and service level of toll plaza (Xiao et al., 2008), thus it has been widely used in many countries. In China, approximately 12% ETC lanes undertake 29.1% volumes during peak hours (Gao De, 2016).

However, due to the limited proportion of ETC vehicles, most toll plazas in the world consist of a combination of MTC lanes and ETC lanes. According to the classification (Abuzwidah and Abdel-Aty, 2015), there are two major designs of this kind of toll plaza. Fig.1(a) shows the design of a traditional mainline toll plaza (TMTP), which has MTC and ETC lanes throughout the tollbooth. This design requires vehicles to decelerate or stop so that drivers can navigate through different toll lanes (MTC or ETC lanes). Fig.1(b) displays the design of hybrid mainline toll plaza (HMTP), in which the MTC and ETC vehicles are completely separated from the upstream of toll plaza. The ETC
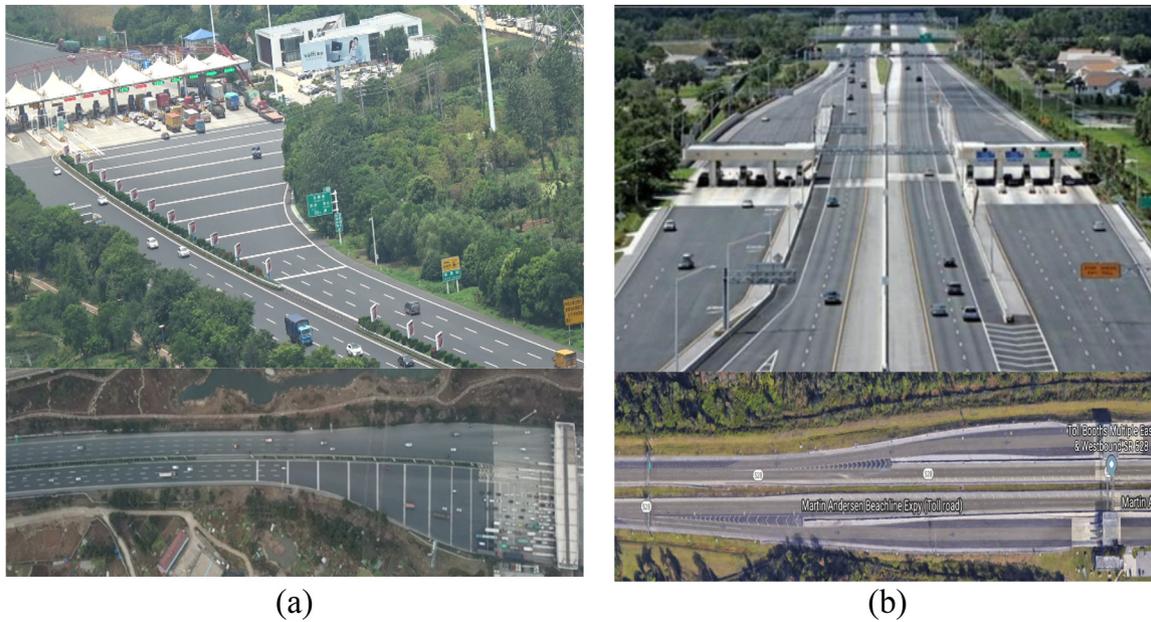
Fig. 1. The different designs of toll plaza area. (a) The design of traditional mainline toll plaza; (b) The design of hybrid mainline toll plaza (*Source:* Central Florida Expressway Authority& Google map).

vehicles can pass directly with minor delay if at all from open road tolling (ORT) lanes. The HMTP are widely used in the United States, while the TMTP are more popular in other countries, including China, Korea, England, etc.

Although this hybrid design can improve the traffic capacity, collision risk might also increase. As shown in Fig. 2, in the whole diverging area, vehicles are required to decelerate, navigate to the targeted toll collection lanes, and complete the diverge behavior rapidly. Due to the limited available space and various configurations of toll collection lanes, drivers may suffer from sudden weaving maneuvers and frequent crossing behaviors, which substantially increase the collision risk in the diverging area remarkably (Abuzwidah et al., 2014). Furthermore, the mixed traffic consisting of MTC and ETC vehicles are more complex, and the non-lane marking of road could lead the diverging behaviors to be unordered and unpredictable. Thus, vehicles are particularly risky in this area. Previous studies verified the higher crash risk in toll plaza area. Abdelwahab and Abdel-Aty concluded that the higher speed of ETC vehicles and speed variation between MTC and ETC vehicles could increase crash probability at toll plazas and lead to more severe

accidents (Abdelwahab and Abdel-Aty, 2002). Also, the various lane configurations and toll collection types may confuse drivers (Carroll, 2016; Mckinnon, 2013). The TMTP is especially dangerous due to more complex traffic conditions, compared to the HMTP (Abuzwidah and Abdel-Aty, 2015). Considering the large number of TMTP worldwide, safety issues is vitally important and worthy of investigation.

Thus, in this study, we take a toll plaza in Nanjing, China as an example, and focus on the safety evaluation of up stream toll plaza area (toll plaza diverging area). A layout and potential conflicts are expressed in Fig. 2. Along the driving direction, the study area can be divided into three parts, i.e. main lanes, diverging area, and toll collection lanes (tollbooths). The ETC lanes are located on the leftmost side while the MTC vehicles pass through right-side lanes and the rightmost two MTC lanes are only utilized by trucks. Usually, the number of ETC lanes are fewer than that of MTC lanes and the number of ETC lanes of each toll plaza usually ranges from 1 to 3. According to many observations, it can be found that the majority of vehicles start to diverge at the lane marked road where locates the last traffic sign (toll collection sign), so in this study, we define the toll plaza diverging area as
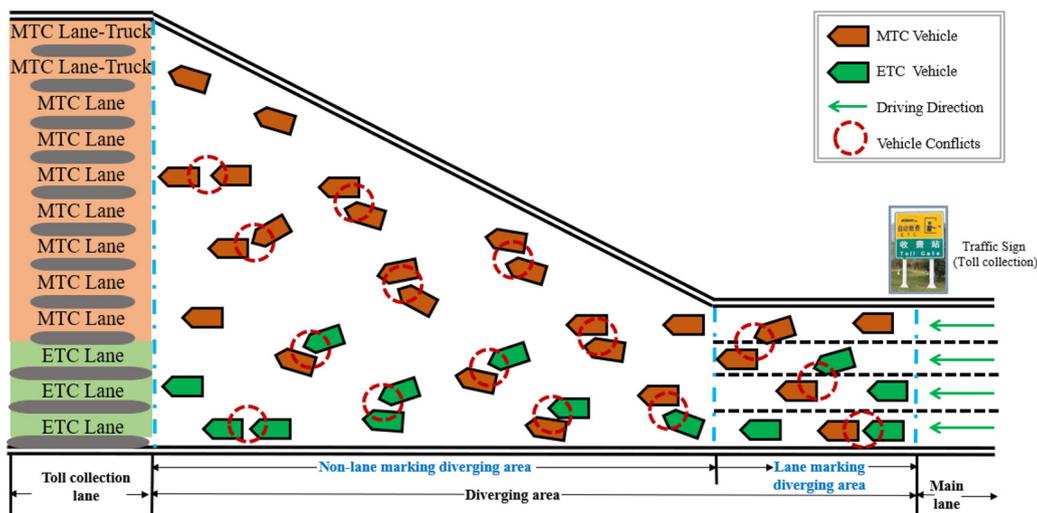

Fig. 2. Layout of toll plaza diverging area of TMTPs and illustration of potential conflicts (study site).

Fig. 3. Layout of toll plaza diverging area and toll collection lanes (study site).

consisting of two parts: lane marked diverging area and non-lane marked diverging area. The lane marked diverging area are connected to main lanes, as well as the widen area without lane marking.

Although many previous studies have been focused on the efficiency and performance of toll plaza, limited studies have been conducted on the safety of it. Among the existing researches about toll plaza's safety, Abuzwidah and Abdel-Aty (Abuzwidah et al., 2014; Abuzwidah and Abdel-Aty, 2015) collected historical crash data and evaluated the safety of three different kinds of toll plaza by using before-after studies. Carroll (Carroll, 2016), Valdés (Valdés et al., 2017), and Saad (Saad et al., 2018) explored risky driving behaviors at expressway toll plaza by using the driving simulator and investigated the effects on vehicle safety of various factors, such as paths, signs, pavement markings, segment lengths, and traffic conditions of toll plaza and demographic characteristics of driver. The microscopic simulation model of toll plaza was also conducted to investigate the safety of toll plaza using simulation software, such as VISSIM (Hajiseyedjavadi et al., 2015; Mckinnon, 2013) and PARAMICS (Mudigonda Graduate Student et al., 2008; Nezamuddin and Al-Deek, 2008). Moreover, because the entire toll plaza has a large area, so the diverging behaviors at this area is a long process that could result in the differences of collision risk among different parts of the toll plaza area. Limited previous studies have considered those differences, it is recommended to compare the vehicle safety in different parts of toll plazas.

The data used in the abovementioned studies are mainly from historical crash data or simulation results, while hardly any research has evaluated the vehicle collision risk using the actual vehicle trajectory data. However, it is hard to record an adequate number of crashes over a short period of time to conduct an effective safety evaluation, and the publicly available crash data are not reliable and authentic in many countries, including in China. Moreover, the simulation data is unrealistic which cannot represent the naturalistic driving behaviors. Especially in the toll plaza, the traffic situation is fairly complicated and it is hard to simulate this area. According to the discussions in previous studies, Traffic Conflict Techniques (TCTs) has been recognized as a better proactive surrogate approach to analyze traffic safety problems. Compared to the traditional approach, the TCTs can increase the possibility of: (i) shorten the safety evaluation time and improve the efficiency; (ii) consider the information on the behavioral aspects into vehicle collision; (iii) a better understanding into the failure mechanism and chain of events which leads to road traffic collisions and resulting consequences (Guo et al., 2016; Laureshyn et al., 2010; Mahmud et al.,

2017; Sayed and Zein, 1999; Zheng et al., 2014a, 2014b).

In consequence, this study aimed to fully explore the traffic safety in the entire toll plaza up stream diverging area. To achieve this objective, we used an Unmanned Aerial Vehicle (UAV) to collect video data at a typical toll plaza in Nanjing, China. The vehicle trajectory data was extracted from the video using an automated analysis system, which provides better understanding of detailed and realistic driving behavior. The vehicles' collision risks were evaluated using the extended Time-to-Collision indicator, which established the relation between microscopic vehicle trajectory data and collision risk. Subsequently, the impacts of the vehicles' toll collection type, target lane and location on safety were compared. Finally, a random parameters logistic model was estimated to quantify the impact of the different factors on vehicle collision risk, including the vehicle individual factors, factors of diverging area, and factors of traffic flow. This study contributes to the literature by investigating the critical safety issues at toll plaza diverging areas, and the findings provide useful information for highway safety improvement.

2. Data

2.1. Video-data collection

To investigate the traffic conflicts at toll plaza diverging area, we conducted a field survey in Nanjing, the capital city of Jiangsu Province in eastern China. A representative study site located on G42 expressway was selected for analysis. G42 is an east-west direction toll way with eight lanes, serving as a major corridor in the northeast area of Nanjing city. This toll plaza has a diverging area per direction and the westbound diverging area of this toll plaza was chosen as the study site.

Fig.3 shows the layout of this diverging area. The length of the diverging area is about 360 m, including 60 m lane marked diverging area and 300 m non-lane marked diverging area. The width of lane marked diverging area is about 15 m. The non-lane marked diverging area is widened from 15 m to 65 m within the 300 m length. There are 4 lanes of lane marked diverging area, and 3 ETC lanes and 9 MTC lanes of the toll collection lanes. In the diverging area, vehicles from the 4 lanes of main lane have to diverge into twelve toll collection lanes in this 360 m-length diverging area, which increases the diverging behaviors and potential for traffic conflicts. Note that, MTC trucks need to diverge into the rightmost two MTC toll lanes and MTC passenger cars could pass through the other seven MTC toll lanes in the middle.

In this study, vehicle data were collection by video recording by Unmanned Aerial Vehicle (UAV). The drone can provide 4 K ultra high definition and 30 frames per second (fps) video. Using this method to collect vehicle data has several advantages, such as the richness of extracted data, and the relatively low cost (Saunier et al., 2011). Most importantly, the video provides microscopic vehicle trajectory data which can extract naturalistic movements of vehicles (Meng and Weng, 2011).Furthermore, recording video from the top view by drone can reduce errors compared with recording video from a top of building, which has the issue of oblique observations and easily causes errors in the process of coordinate transformation and camera calibration (Kaufmann et al., 2018).

Field data collection was conducted during the peak periods on March 17, 2018. About 1.5 h videos were recorded under sunny weather and 50 min videos were selected for analysis. The flight height was about 200 m and approximately 400 m long of the road was captured. Based on the collected traffic data, the equivalent hourly traffic flow rate is calculated as 6 times of the 10-minute volume. The traffic flow rate of this diverging area ranged from 1050 vph to 1740 vph.

2.2. Video-data processing

2.2.1. Features detection and tracking

An automated video data analysis system based on OpenCV (Open Source Computer Vision, an existing open-source tracking tool) was used in this study, which includes various computer vision algorithms and has been widely used in the computer vision processing. According to the features of our video samples, we developed this analysis system by the tracking by detection' algorithm (Zangenehpour et al., 2015) to handle partial feature tracks in toll plaza diverging area. The object detection is done using template matching which is a technique for finding areas of an image that match (are similar) to a template image (patch) (GitHub, 2018; OpenCV, 2017). Based on it, individual pixels can be detected by each frame and recorded as trajectories automatically. We utilized a flowchart to summarize the process, as shown in Fig. 4.

As shown in Fig.4, an analysis area was chosen in the video footage before the video processing. When a vehicle appears in the video footage rather than analysis area, it will be manually marked out at first and then be automatically detected by each frame. Meanwhile, the vehicle type and toll collection type will be classified manually. The method has been widely applied in previous studies (Guo et al., 2017, 2016; Ismail et al., 2013; Saunier et al., 2010; Zangenehpour et al., 2015).

The accuracy of this automated tracking algorithm was validated by manual detection of a subset of 50 vehicles randomly selected from the video. For each vehicle, we detected it at 10 different frames manually when it was travelling in the toll plaza diverging area. Thus there is a

total of 500 detection results (ground truth). We also utilized the tracking algorithm to detect these vehicles automatically and get the detection results (test results) of each frame, so the real results and test results can be paired by each frame. Then the intersection over union (IoU) was employed to evaluate the accuracy of test results (Rosebrock, 2016). As shown in Fig. 5, the predicted bounding box was the output of automatic tracking algorithm (the test results) and the ground truth bounding box was the output of manual detection (the real results). As shown in Eq. (1), IoU is the intersection area divided by the union area of the two bounding boxes. Generally, if the IoU ≥ 0.5, the detection is recognized as correct. Through this method, we validated our tracking algorithm and the results indicated an accuracy of 93.8% (469/500), which is good enough for our research.

$$IoU = \frac{Area\,of\,Overlap}{Area\,of\,Union} \tag{1}$$

Because of the high stability of the tracking, vehicle trajectory can be extracted completely. And in order to guarantee the higher accuracy, the analysis system allows the user to acts as a supervisor and pauses the process to redetect vehicles manually when the system loses vehicle tracking. About 96% (1103 of 1152) vehicles were tracked and their complete trajectories were obtained.

2.2.2. Coordinate transformation and error elimination

The coordinate transformation has been also carefully considered in this study. Generally, the transformation is a mapping between the real world (three dimensional) and the image space (two dimensional), which is described by a relationship matrix of a fixed point in image and the reference image. More details of the transformation models can be referred in previous studies (Ismail et al., 2013; Vincent and Laganiere, 2001; Wang et al., 2016).

In this paper, we utilized the unmanned aerial vehicle (UAV) to collect data. For the video image recorded by the UAV, the road surface's height differences are relatively small compared to the flight height of UAV. Therefore, the coordinate transformation can be simplified as a homography transformation problem. More details of the homography transformation models can be referred in previous studies (Nejadasl and Lindenbergh, 2014; Vincent and Laganiere, 2001; Wang et al., 2016).

For this model, at least four corresponding points are required for calibration, in which three of them cannot be collinear. The selected points should also be able to cover the whole image. Moreover, considering the impact of the wind, the UAV flying in the air may have jitter. The jitter could result in the errors of vehicle's trajectory, so the camera motion should be separated and eliminated from the vehicle motion in the video. In that case, the coordinate transformation has to be conducted on each frame.

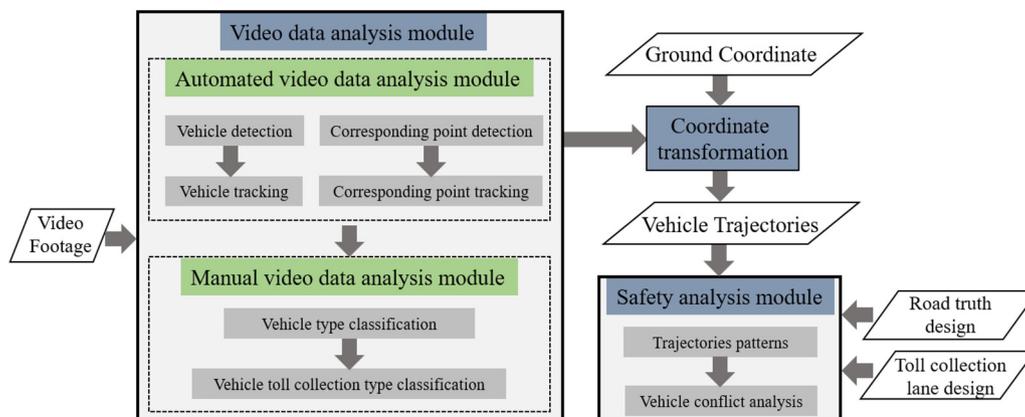In our research, we followed the above process to accomplish the

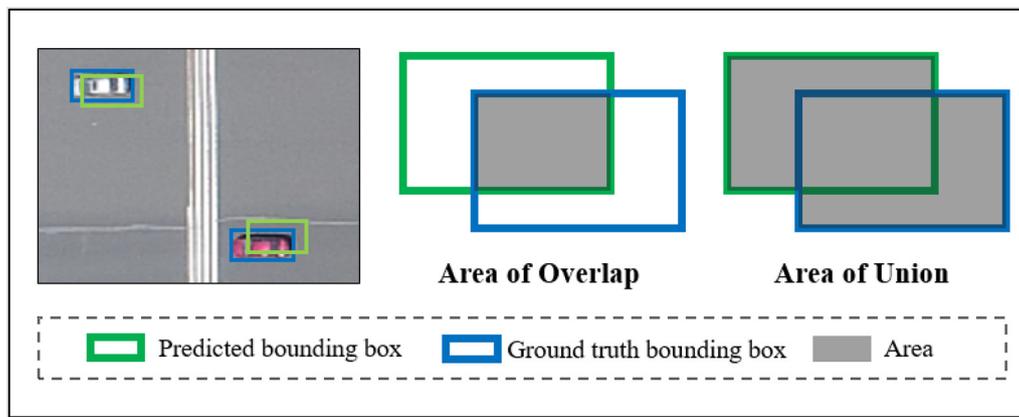**Fig. 4.** The flowchart of video data processing.

Fig. 5. Illustration of Area of Overlap and Area of Union.

coordinate transformation. Eight corresponding points were selected and tracked to improve the accuracy of transformation. A difference is when we tried to compare coordinates of the corresponding points on video images of distinct frames, the changes were very small, which indicated the impact of the jitter is tiny. The possible reason may be that we collected the video by UAV on a calm and windless day and the advanced UAV also has a fairly good stability performance. In this case, we only needed to choose a frame of image as the basic one and finished calibration of the coordinate transformation model depended it. Furthermore, to measure the accuracy of the transformation, we randomly selected another 20 points for validation. The real-world coordinates of these points were utilized to find the best transformation model. With the best one, the coordinate differences between real-world and tested coordinates were all smaller than 2.5 m, which were good enough considering the length of studied site (i.e., 360 m).

Note that, due to the stochastic errors of this data analysis system, the raw position from the video are always scattered around the "true" trajectory (Takeda et al., 2007). Therefore, a moving average filtering (low pass filtering) was applied to smooth the trajectories and eliminate tracking noise, which can reduce the noise influence on the TTC calculation (Kaufmann et al., 2018).

2.2.3. Data obtaining

After the video data processing and error elimination, the precise trajectory of each vehicle could be obtained. The information automatically extracted from the videos is the centroid coordinate of vehicle i at time t, $O_t(i)$, the Vehicle type (car, truck, bus) and Vehicle toll collection type (MTC&ETC) were extracted manually. Furthermore, we calculated the speed of vehicle i at time t, $V_t(i)$ (m/s) and the angle of vehicle i at time t between the X-axis and velocity direction, $\theta_t(i)$.

In this study, the vehicle type is divided into three categories: car, bus (heavy passenger vehicle) and truck. Also, vehicles are divided into two categories according to their toll collection type: MTC vehicle and ETC vehicle. As shown in Table1, there are 635 (57.52%) MTC vehicles and 468 (42.48%) ETC vehicles. The percentages of car, bus and truck are 93.48%,2.72% and 3.80% respectively.

Table 1
The number of vehicles with different vehicle types.

Category	Type	Sample size	Proportion (%)
Vehicle Type	Car	1031	93.47
	Bus	30	2.72
	Truck	42	3.81
Vehicle Toll Collection Type	MTC	635	57.57
	ETC	468	42.43

3. Methodology

3.1. Time-To-Collision

3.1.1. Basic time-to-Collision

The application of Traffic Conflict Techniques (TCTs) for analyzing traffic safety problems has gained acceptance as a proactive surrogate approach (Perkins and Harris, 1968; Sayed et al., 2013; Zheng et al., 2014a).Various conflict proximal surrogate indicators have been developed to measure the severity of a traffic conflict. Mahmud (Mahmud et al., 2017) and Tarko (Tarko et al., 2009) comprehensively compared the development and application of different indicators in their researches. Among all proximal surrogate indicators, Time-To-Collision (TTC) has been most widely used as an effective safety indicator in estimating the individual vehicle collision risk (Cai et al., 2018; Li et al., 2017b; Weng et al., 2015).

TTC is defined as the time required for two vehicles to collide if they continue at their present speed and along the same path (Hayward, 1972). The TTC of a following vehicle i at time step t with respect to the leading vehicle (i-1) can be calculated as Eq. (2):

$$TTC_i(t) = \begin{cases} \frac{X_{i-1}(t) - X_i(t) - L_i}{V_i(t) - V_{i-1}(t)}, & if\ V_i(t) > V_{i-1}(t) \\ \infty, & if\ V_i(t) \leq V_{i-1}(t) \end{cases} \quad (2)$$

where $X_i(t)$ denotes the position of the vehicle i at time t, $V_i(t)$ is the speed of the vehicle i at time t, and L_i is the length of vehicle i. According to the definition, lager TTC could provide more time for driver to avoid collision, which results in smaller probability of traffic collisions. In contrast, a smaller TTC could result in a higher probability of risks (Li et al., 2017a, 2016).

3.1.2. Extended time-to-Collision using vehicle trajectory data

The conventional TTC has been widely used in many previous studies, however, most studies calculated TTC based on the assumption that the consecutive vehicles are in the same traffic lane or their trajectories cross at a right angle (Behbahani and Nadimi, 2015; Laureshyn et al., 2010; Mahmud et al., 2017). As mentioned above in Section 1, vehicles need to finish diverging maneuvers mandatorily in the toll plaza diverging area and could approach each other at any angle, especially in the non-lane marked diverging area. Therefore, the conventional TTC is not suitable for conflicts analysis in this study. To eliminate this limitation, we utilized the extended TTC to evaluate the vehicles' conflicts in the toll plaza diverging area. It is an extension of the conventional TTC to the more general case of two-dimensional movement, so its applicability is more widely used for various traffic situations (Ward et al., 2015).

As shown in Fig.6, two vehicles are considered with vector positions (O_i,Oj,C_i,Cj) and velocities (V_i,Vj) in the plane. In this study, O_i and Oj
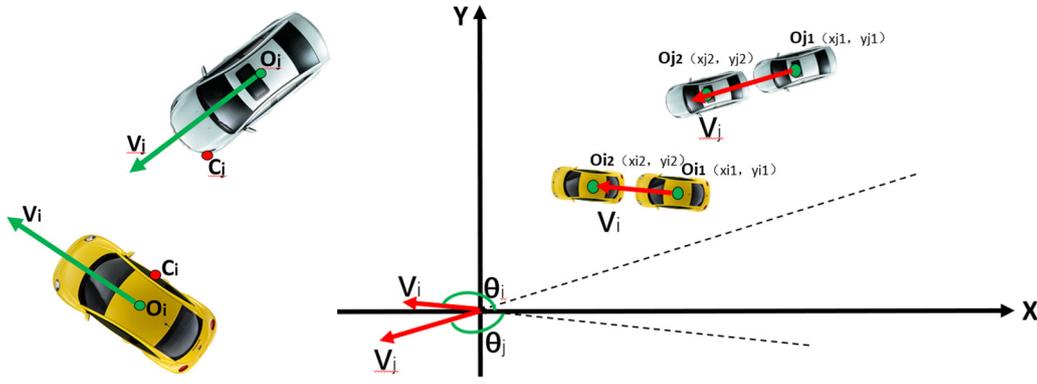
Fig. 6. Illustration of two vehicles' positions when they are approaching.

are defined as position vectors of vehicle centroids, D_{ij} is the separation between the two vehicles' centroids. C_i and C_j are position vectors of the closest points of the two vehicles at the given time step, d_{ij} is the separation between the two closest points. During the whole diverging behavior, the movement of vehicles are consecutive, so the point of vehicle moving smoothly from time step to time step.

Because the collision points are on the outer edge of vehicles, so the closest points could collide each other at first. The separation between the two closest points of vehicles, d_{ij}, is given in Eq. (3):

$$d_{ij}^2 = \|C_i - C_j\|^2 = (C_i - C_j)^T(C_i - C_j) \tag{3}$$

Then, we can get Eq. (4) by differentiating both sides of Eq. (3):

$$d_{ij}\dot{d}_{ij} = (C_i - C_j)^T(V_i - V_j) \tag{4}$$

The first derivative of the separation is $\dot{d}_{ij}$, the approach (closeness) rate is $-\dot{d}_{ij}$. The approach rate is the relative speed between the two vehicles to collide. To summarize, the separation between Vehicles i and j and its first derivative can be computed as follows:

$$d_{ij} = \sqrt{(C_i - C_j)^T(C_i - C_j)} \tag{5}$$

$$\dot{d}_{ij} = \frac{1}{d_{ij}}(C_i - C_j)^T(V_i - V_j) \tag{6}$$

The TTC is investigated at a given time step in this study, so we assume that the approach rate between two vehicles is constant. According to the definition of TTC, when a collision between two vehicles would have occurred, the TTC is:

$$d_{ij} + \overset{\text{bull}}{d}_{ij} \cdot \text{TTC} = 0; \quad \text{TTC} = -\frac{d_{ij}}{\overset{\text{bull}}{d}_{ij}} \tag{7}$$

Moreover, due to the vehicle position data extracted from video is a position vector of vehicle centroid, which cannot be regarded as the closest points of two vehicles. Instead, we need to replace the C_i and C_j with O_i and O_j in Eq. (3). As shown in Fig.6, the separation between two vehicles' centroids (D_{ij}) is longer than the separation between two closest points (d_{ij}). However, the difference between D_{ij} and d_{ij} is not easily to be measured because it varies by changes of the approaching angle. Therefore, in order to ensure that all potential traffic collisions could be considered in this study, we assume that the difference between D_{ij} and d_{ij} is the sum of half of the length of the leading vehicle (L_l) and half length of the following vehicle (L_f). The d_{ij} can be calculated as:

$$d_{ij} = D_{ij} - 0.5L_l - 0.5L_f \tag{8}$$

According to the analysis above, D_{ij} and $\dot{D}_{ij}$ can be calculated by Eq. (9) and Eq. (10). In Eq. (10), the approach rate of two vehicles' centroids ($\dot{D}_{ij}$) can be assumed the same as the approach rate of two vehicles' closest points ($\dot{d}_{ij}$).

$$D_{ij} = \sqrt{(O_i - O_j)^T(O_i - O_j)} \tag{9}$$

$$\overset{\text{bull}}{D}_{ij} = \overset{\text{bull}}{d}_{ij} = \frac{1}{D_{ij}}(O_i - O_j)^T(V_i - V_j) \tag{10}$$

In summary, the TTC can be calculated as:

$$\begin{aligned}
\text{TTC} &= -\frac{d_{ij}}{\overset{\text{bull}}{d}_{ij}} = -\frac{D_{ij} - 0.5L_l - 0.5L_f}{\frac{1}{D_{ij}}(O_i - O_j)^T(V_i - V_j)} \\
&= -\frac{\sqrt{(O_i - O_j)^T(O_i - O_j)} - 0.5L_l - 0.5L_f}{\frac{1}{\sqrt{(O_i - O_j)^T(O_i - O_j)}}(O_i - O_j)^T(V_i - V_j)}
\end{aligned} \tag{11}$$

In previous studies, the TTC threshold (TTC*) was widely used to distinguish unsafe situations from safe ones. Vehicle pairs with TTC lower than TTC* are considered as involved in collisions. Previously, researchers have suggested that the threshold TTC* vary from 2 to 4 s (Li et al., 2017a, 2014; Meng and Qu, 2012). In this study, TTC* is set as 4 s (Guo et al., 2016; Osama and Sc, 2015), and the time step is set to be 0.1 s (counting by 3 frames).

3.2. Model formulation

3.2.1. Factors affecting collision risk at toll plaza diverging area

According to the above-mentioned vehicle diverging behaviors at the toll plaza diverging area, it is a long process compared with an action in an instant, and the positions of traffic conflicts could be randomly distributed in the whole area. In order to fully explore the difference of traffic conflicts at the various parts of the diverging area, we divided the study area into twelve segments according to the vertical lane marking and the length of area. The length of each segment is 30 m. As shown in Fig.7, the sequence number ascends along the driving direction. The first two segments are lane marked diverging areas, the others are non-lane marked areas. Note that, as shown in Fig.7, the twelve toll collection lanes are aggregated into four target lane groups, there are three lanes of each group. Lanes of Target Lane group 1 are ETC lanes and that of Target Lane group 2, 3, 4 are MTC lanes (Target Lane group 4 includes 2 toll collection lanes for trucks).

As mentioned above, we can estimate the individual vehicle collision risk using extended TTC and determine whether the vehicle is at risk of being involved in a collision. Therefore, the following vehicle in each diverging area segment can be divided into two cases: (i) "Has the potential collision", if one or more TTC values of the following vehicle are less than TTC*; (ii) "Doesn't have the potential collision", if not. In this study, the following candidate variables in Table 2 that may affect the vehicle collision risk at toll plaza diverging area are considered.

To estimate the mixing severity of MTC and ETC vehicles in a diverging area segment, we extended the application of Entropy Index which is a measure of land use mix originally and denoted as $\text{FMIX}_{\text{MTCETC}}$. This index takes into account the relative percentages of
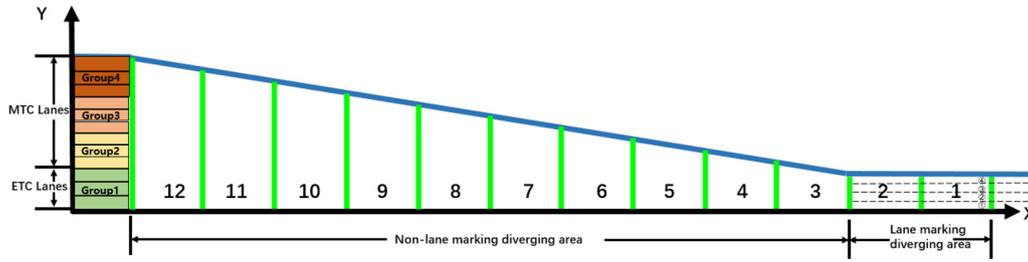
Fig. 7. Layout of diverging area segments and target lanes of the study site.

different types of vehicles within an area. As shown in Eq.(12), P*j* is the percentage of each type *j* in the area, and k (≥ 2) is the number of vehicle toll collection type *j*. It varies from 0 to 1, and higher levels of it correspond to greater mixture (Song et al., 2013). In this study, there are two vehicle toll collection types (k = 2), so when the percentage of each type of vehicles is 50%, the FMIX$_{MTCETC}$ will reach the highest value.

$$FMIX_{MTCETC} = -\left[\sum_{j=1}^{k} P_j \ln(P_j) \right] / \ln(k) \quad (12)$$

3.2.2. Random parameters logistic regression model

Based on the two cases of following vehicle in each diverging area segment, we can determine whether the following vehicle has a potential collision: $y_n = 1$ (Has the potential collision) and $y_n = 0$ (Doesn't have the potential collision), n = 1, 2,…, i*m. Let i and m denote the number of vehicles and the number of diverging area segments respectively, "i*m" can indicate the total number of observations. A binary logistic model can be employed to estimate the vehicle collision risk in the toll plaza diverging area. The conditional probability of vehicle potential collision ($p(y_n)$) can be calculated by Eq. (13):

$$p(y_n) = \frac{e^{g(y_n)}}{1 + e^{g(x_n)}} \quad (13)$$

The logistic regression model is given in Eq. (14):

$$g(y_n) = ln \frac{p(y_n)}{1 - p(y_n)} = \boldsymbol{\beta x} + \varepsilon_n = \beta_{0n} + \beta_{1n}X_{1n} + \beta_{2n}X_{2n} + ... + \beta_{Kn}X_{Kn} + \varepsilon_n \quad (14)$$

Where $\boldsymbol{x}$ is a set of the independent variables that can be either categorical or continuous and $\boldsymbol{\beta}$ is a set of corresponding parameters. The term k is the number of independent variables and ε_n is the error term with a normal distribution with mean zero (Wu et al., 2018). Considering the heterogeneity across observations, random parameters are introduced to the above model. The random parameters in the logistic model can be shown as Eq. (15):

$$\beta_i^{'} = \beta_i + \omega_i, \quad \omega_i \sim N(0, \sigma_i^2) \quad (15)$$

Where $\beta_i^{'}$ is the random parameter varying with different vehicles, β_i is the fixed parameter of ith vehicle, ω_i is a randomly distributed term which follows $N(0, \sigma_i^2)$. In this study, it is assumed that the same variable has the same effects on the dependent variable in different diverging area segments. The findings of many previous researches

Table 2
Candidate variables and variables' explanations.

Category	Variable	Variable Explanation
The individual factors of the following vehicle i	$V_{type}(i)$	An indicator variable for vehicle types, V_{type} = 1 for a car, V_{type} = 2 for a bus and V_{type} = 3 for a truck.
	$VTC_{type}(i)$	An indicator variable for vehicle toll collection types, VTC_{type} = 0 for a MTC vehicle, VTC_{type} = 1 for an ETC vehicle.
	$VL_{initial}(i)$	An indicator variable for initial lanes of vehicle when it enters the toll plaza diverging area, $VL_{initial}$ (1~4) is numbered from left to right of vehicles' driving direction.
	$VL_{target}(i)$	An indicator variable for vehicle target toll collection lanes when it exits the toll plaza diverging area. In this study, the twelve toll collection lanes are aggregated into 4 target lane groups, VL_{target} (1~4) is numbered from left to right of vehicle driving direction.
	$V_v(i)$	The vehicle average speed in the total diverging area, m/s.
	$V_{vstd}(i)$	The standard deviation of vehicle speed in the total diverging area, m/s.
	$VAC_{max}(i)$	The maximum vehicle acceleration in the total diverging area, m/s^2.
	$VDE_{max}(i)$	The maximum vehicle deceleration in the total diverging area (positive number), m/s^2.
	$VAC_{std}(i)$	The standard deviation of vehicle acceleration in the total diverging area, m/s^2.
	$VDE_{std}(i)$	The standard deviation of vehicle deceleration in the total diverging area (positive number), m/s^2
The factors of the diverging area segment in which vehicle i is traveling	$S_{NO}(i)$	An indicator variable for sequence number of the diverging area segments, it is number from 1 to 12.
	$S_w(i)$	The average width of the diverging area segment, m.
	$S_{LM}(i)$	An indicator variable for lane marking features of the diverging area segment, S_{LM} = 0 for non-lane marked, S_{LM} = 1for lane marked.
The factors of traffic flow in the diverging area segment during the entry and exit period of vehicle i	FVO (i)	The average traffic volume of the diverging area segment, vph.
	$FP_{ETC}(i)$	The percentage of ETC vehicles among total vehicles in the diverging area segment.
	$FMIX_{MTCETC}$ (i)	The mix measure of MTC and ETC vehicles in the diverging area segment.
	$FP_{car}(i)$	The percentage of cars among total vehicles in the diverging area segment
	$F_v(i)$	The vehicle average speed of total vehicles in the diverging area segment, m/s.
	$F_{vstd}(i)$	The standard deviation of total vehicles' speed in the diverging area segment, m/s.
	FAC(i)	The average vehicle acceleration of total vehicles in the diverging area segment, m/s^2.
	FDE(i)	The average vehicle deceleration of total vehicles in the diverging area segment, m/s^2.
	FAC_{std} (i)	The standard deviation of total vehicles' acceleration in the diverging area segment, m/s^2.
	FDE_{std} (i)	The standard deviation of total vehicles' deceleration in the diverging area segment, m/s^2.

supported that random parameters logistic model can improve the model performance compared with the traditional model (Shi and Abdel-Aty, 2015; Wu et al., 2018; Yuan et al., 2018).

Bayesian approach is adopted to estimate the posterior distribution of parameters, it can provide better fit and reduced uncertainty for parameter estimations than the frequent approach (Ahmed et al., 2012). Due to not all the parameters should be considered as random parameters, it is necessary to test the model multiple times to obtain the best performance. The indicators DIC (Deviance Information Criterion) and AUC (the area under Receiver Operating Characteristic (ROC)) are used to estimate the model performance. The model with smaller DIC or bigger AUC is preferred (Yuan et al., 2018).

4. Results and discussion

4.1. Comparison results of conflicts for vehicles with different toll collection types

As discussed above, MTC and ETC vehicles need to choose different toll collection lanes located in the distinct positions at the end of toll plaza diverging area, also the limited speed of toll collection lane varies for different types (ETC lane's limited speed > MTC lane's limited speed). Therefore, the diverging behavior of vehicles with different toll collection types may have differences. In this subsection, the conflicts of MTC and ETC vehicles were compared. Fig.8 shows the conflicts (TTC ≤ 4 s) spatial distribution of vehicles in the total 50-minutes video. Note that the conflict in this figure was calculated every 0.1 s, so this figure shows the collection of conflict points. As shown in this figure, there are significant differences of the conflicts spatial distributions between ETC vehicles and MTC vehicles. Moreover, the variance test was conducted to validate whether there are significantly different effects of these two categories on TTC (< 0.001), and the result also indicate the differences.

As shown in Table 3, totally, about 78% of MTC vehicles and 82% of ETC vehicles were involved in potential collisions at least one time in the whole toll plaza diverging area. According to the definition of the dependent variable in the model, the total sample size is 13,236. The dangerous sample size for all vehicles (samples with potential collision) are 4213 (31.83%), and for MTC and ETC vehicles are 2372 (31.13%) and 1841 (32.78%), respectively. Further, the average value of TTC for the ETC vehicles (2.18 s) is smaller than that of MTC vehicles (2.33 s). From the comparison, ETC vehicles are more at risk at toll plaza diverging area than MTC vehicles, which may be due to the higher speed of ETC vehicles than that of MTC vehicles.

Although the possibility of traffic collision can be estimated by TTC, the vehicle diverging behavior in the whole studied area is a long process. Hence, it is necessary to analyze the duration of each vehicle in the danger status. An aggregated indicator was developed to estimate the total time exposed to dangerous status of the vehicle, denoted as DT (Dangerous Time). It can be calculated by Eq. (16):

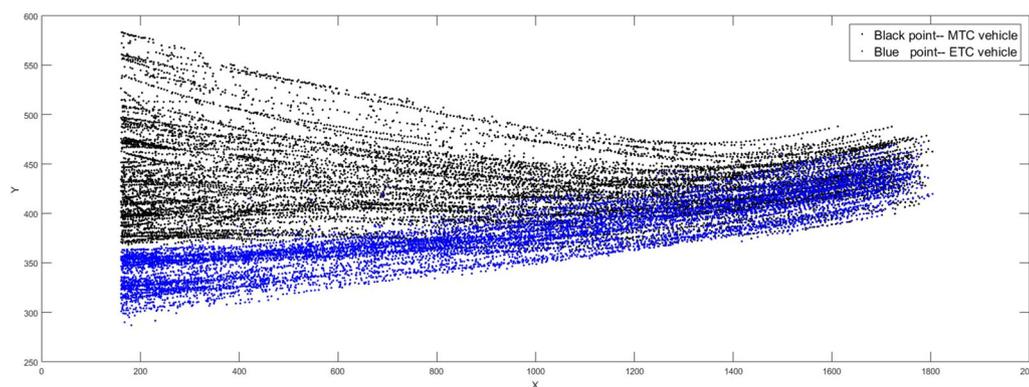$$DT_i = N_i \cdot \Delta t \tag{16}$$

Where N is the frequency of TTC which is less than TTC* of vehicle i, Δt is the time step. Overall, each vehicle needs about 18.84 s to pass the toll plaza diverging area, in which the average dangerous time is 3.38 s. The average DT of MTC (3.17 s) is smaller than that of ETC (3.52 s). The results indicated that ETC vehicles are not only more likely to be involved in collisions but also have higher duration.

Additionally, the study site has twelve toll collection lanes. These lanes provide more options for vehicles to pass the toll plaza, so the vehicles passing by different toll collection lanes may have different diverging behavior as well as collision risk. In this study, we divided vehicles into four groups according to their toll collection types and target toll collection lanes. The four groups are (see Fig.7 for details):

- Group1: ETC-Target Lane1, ETC vehicles whose target toll collection lanes belong to Target Lane group1;
- Group2: MTC-Target Lane2, MTC vehicles whose target toll collection lanes belong to Target Lane group2;
- Group3: MTC-Target Lane3, MTC vehicles whose target toll collection lanes belong to Target Lane group3;
- Group4: MTC-Target Lane4, MTC vehicles whose target toll collection lanes belong to Target Lane group4.

As shown in Fig.9 (a), the dangerous sample size of Group1 (ETC-Target Lane1) is the highest with a very high value of 1,841, compared to the other groups.

However, the proportion of dangerous sample size shows vehicles in Group2 have the highest collision risk. Specifically, the proportion of dangerous sample size of Group2 (34.98%) is higher than that of Group1 (32.78%) which is followed by Group4 (31.57%) and Group3 (27.00%). Fig.9 (b) shows the distribution of TTC values of these four groups. The average TTC of the dangerous sample of Group1 is minimum compared to the other three groups. It indicates that the collisions of ETC vehicles could be more serious than that of MTC vehicles. This finding is intuitively reasonable because of the higher speed of ETC vehicle.

4.2. Comparison results of conflicts for vehicles in different diverging area segments

As mentioned in subsection 3.2.1, the total toll plaza diverging area was divided into twelve segments. In this subsection, the conflicts in different area segments are compared and results are shown in Fig.10. The frequency of dangerous samples has a rising trend among these twelve segments. Segment 1 has the smallest one (115) while the Segment 12 has largest value of 550.

Moreover, both dangerous sample size and dangerous sample density have a slight downward trend among Segment 2 to Segment 12, which indicates vehicle become more dangerous when it is closer to toll collection lanes (except the area Segment 1). A possible explanation is that vehicle's deceleration is larger when it is close to the collection

Fig. 8. Conflicts spatial distribution of vehicles with different toll collection types (TTC ≤ 4 s).

Table 3
Summary of data associated to conflicts for vehicles with different toll collection types.

Statistics	All Vehicles	MTC Vehicles	ETC Vehicles
Quantity of vehicles	1103	635 (57.57%)	468 (42.43%)
Quantity of dangerous vehicles	877 (79.44%)	493 (77.64%)	384 (82.05%)
Total sample size	13236	7620	5616
Dangerous sample size	4213(31.83%)	2372(31.13%)	1841(32.78%)
Average TTC of dangerous sample (s)	2.27	2.33	2.18
Standard deviation of TTC of dangerous sample	1.12	1.09	1.15
Average total traveling time (s)	18.84	19.27	18.26
Average DT (dangerous time) (s)	3.38	3.17	3.52

station. The larger speed differences resulting from decelerations could cause the higher likelihood of conflicts in these areas. Furthermore, when more vehicles are entering into Segment 12, the queuing behavior is more frequent, which also increases the rear-end collision risk. On the other hand, because the gradually widening of road, the area size of each segment has an uptrend when approaching to the toll collection lane, it could result in the decrease of dangerous sample density (dangerous sample size per square meter).

However, when vehicles observe the last traffic sign and just enter the diverging area, drivers may be not ready to diverge, so they would not change lanes at the beginning of the diverging area. As shown in Fig.10, both dangerous sample size and dangerous sample density have a dramatic increase from Segment 1 to Segment 2, it suggests that more vehicles could be involved in collisions in Segment 2.

In addition, to further figure out whether the effects of vehicle toll collection types on collision risk varies by different area segments, dangerous sample size and average TTC of each group in different segments were calculated. As shown in Fig.11, the overall trend of Group1, Group2 and Group3 are similar to the trend in Fig.10. The conflicts of these three groups reach the peak in Segment 12 while Segment 1 is the safest area.

However, it is significant that the dangerous sample sizes of Group4 are less than that of other groups. The majority of conflicts occurred in Segments 3, 4 and 12, and the most dangerous area is Segment 10. The findings are reasonable since vehicles passing by Target Lane 4 are mainly trucks and Target Lane 4 usually has lower volume than other target lanes. Moreover, vehicles passing by Target Lane4 usually are mixed with other vehicles at the beginning of the diverging area and diverge into the right side around the middle of the diverging area. Compared to the forepart, the middle part has lower traffic volume and

traffic flow are less motley, so they are more dangerous at the beginning of the diverging area.

4.3. Modeling results

4.3.1. Modeling results of random parameters model

The number of total observations is 13,236 including 4213 (31.83%) observations which dependent variable value is 1 (has the potential collision). The correlation checking of all the independent variables was adopted before estimating the logistic model, and the results with high correlation are presented in Table 4. The result shows twelve variables (VTC_{type}, $VL_{initial}$, V_{vstd}, VAC_{max}, VAC_{std}, VDE_{std}, S_w, S_{LM}, FP_{ETC}, FP_{car}, FAC, and FAC_{std}) have high correlations with other independent variables. To avoid the error accumulation effects in the logistic model, these twelve variables were excluded in the following model.

The modeling results are shown in Table 5. Both the DIC and AUC values indicate that the random parameters model could consistently provide better model performance than the random effect model. Almost all variables in the random parameters model are significant except the vehicle type of truck, which may be due to the fewer number of truck samples. The parameters of V_{type} (bus vs car), V_v, $FMIX_{MTCETC}$, F_v, F_{vstd} and Intercept have significant standard deviation, which validates the existence of unobserved heterogeneity across the covariates. The two models have the same sign of coefficients.

As shown in Table 5, the absolute value of the coefficient for the V_{type} (bus vs car) is 0.84, so bus has higher probability to be involved in a traffic collision compared to the car. The results of different diverging area segments (S_{NO}) are also consistent with the comparison results in subsection 4.2, it indicates that those following 11 segments are
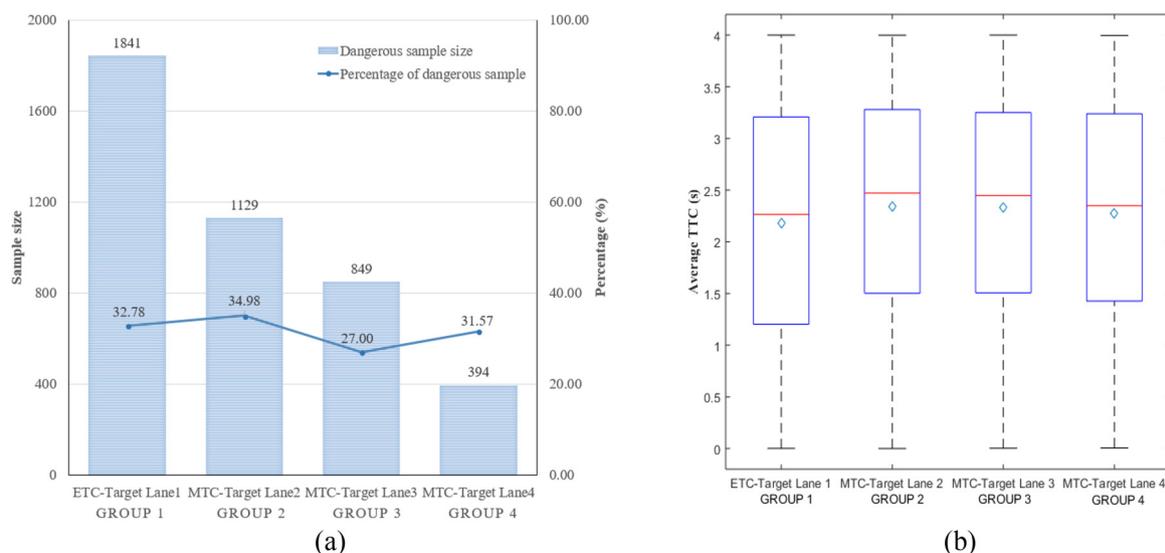

Fig. 9. Conflict analysis of dangerous samples of different vehicle groups, (a) Sample size and percentage of dangerous sample of different groups; (b) TTC values distribution of different groups.
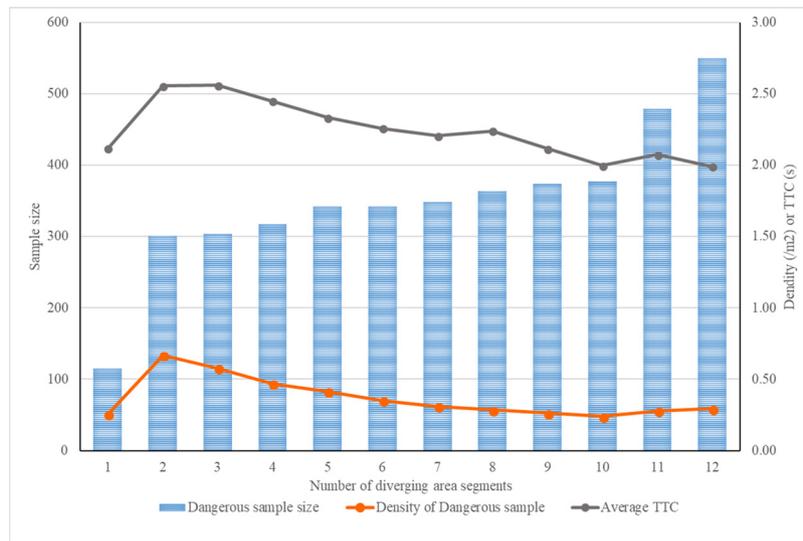
Fig. 10. Conflict analysis of dangerous samples in different area segments.

strongly related to higher collision risk compared to Segment 1.

In addition, the results indicate that the target toll collection lanes of vehicle (VL_{target}) are significant for the collision risk. Compared to passing by Target Lane 1, the collision risk could increase if vehicle's final toll collection lane is Target Lane2, while it could decrease if it passes the toll plaza by Target Lane3 and Lane4. The results are consistent with the comparison results in subsection 4.1. Also, the findings are intuitively reasonable since the left side of the diverging area is more complex with higher traffic volume, MTC and ETC vehicles are mixing in this side of the area which result in the higher frequency of diverging maneuvers. For MTC vehicles with Target Lane2, they pass the diverging area mainly by the left side, so they are more likely to be involved in collisions than Group3 and Group4. Moreover, MTC vehicles need to complete stop at the toll collection lane and usually should wait in queues, so the rear-end conflicts of vehicles in Group2 are more than that of ETC vehicles in Group1.

Furthermore, Vehicles in heavy traffic are easy to be involved in collisions. According to the result of the FVO variable, higher traffic volume could result in higher collision risk. On the other hand, the average vehicle deceleration of surrounding vehicles (FDE) has a

negative effect on the collision risk. This finding is expected since the lower ability to change speed could be observed due to heavy traffic.

Both the average speed (V_v) and the maximum deceleration (VDE_{max}) of each vehicle in the total diverging area have significant effects on the collision risk. The maximum deceleration of each vehicle in the total diverging area is positively associated with the collision risk, while the average speed of vehicle in the total diverging area has a negative effect on the collision risk. The low speed of heavy traffic flow could account for this finding, because more conflicts could be observed for higher traffic volume which is supported by the result of the FVO variable. Likewise, the average speed of total vehicles in the diverging area segment (F_v) has a similar effect on the collision risk and similar reason.

Moreover, if the traffic flow is with higher mix of MTC and ETC vehicles, the risk among this traffic flow could tend to be more dangerous ($FMIX_{MTCETC}$). This result shows that the mix of MTC and ETC vehicles in the same diverging area has the significant effects on vehicle safety.
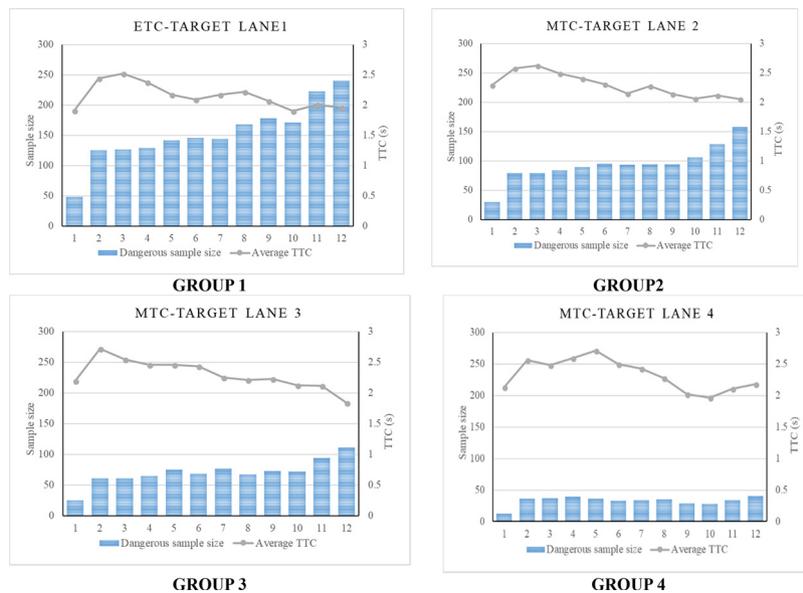

Fig. 11. Conflict analysis of dangerous samples of different vehicle groups in different area segments.

Table 4
Correlation results of independent variables (with high correlation).

Variable	VL_{final}	V_{type}	V_v	VDE_{max}	S_{NO}	FDE	FDE_{std}
VTC_{type}	−0.91						
(Vehicle toll collection types)	<0.001						
$VL_{initial}$	0.53						
(Initial lane of vehicle when it enters the toll plaza diverging area)	<0.001						
V_{vstd}			0.59				
(The standard deviation of vehicle speed in the total diverging area)			<0.001				
VAC_{max}				0.87			
(The maximum vehicle acceleration in the total diverging area)				<0.001			
VAC_{std}				0.86			
(The standard deviation of vehicle acceleration in the total diverging area)				<0.001			
VDE_{std}				0.98			
(The standard deviation of vehicle deceleration in the total diverging area)				<0.001			
S_w					0.99		
(The average width of the diverging area segment)					<0.001		
S_{LM}					0.65		
(Lane marking feature of the diverging area segment)					<0.001		
FP_{ETC}	−0.62						
(The percentage of ETC vehicles among total vehicles in the diverging area segment)	<0.001						
FP_{car}			−0.69				
(The percentage of cars among total vehicles in the diverging area segment during the entry and exit period of vehicle i)			<0.001				
FAC						0.74	
(The average vehicle acceleration of total vehicles in the diverging area segment during the entry and exit period of vehicle i)						<0.001	
FAC_{std}							0.74
(The standard deviation of total vehicles' acceleration in the diverging area segment during the entry and exit period of vehicle i)							

4.3.2. Elasticity effects of random parameters model

The estimated parameters of the independent variables in the above Table 5 do not directly provide the magnitude of the effects of variables on the probability of collision risk. According to the previous studies, the elasticity effect can be interpreted as percentage change in probability of a collision due to a change in the independent variable (Eluru et al., 2008; Guo et al., 2018a). To better understand the impact of contributing factors, we calculated the aggregate level "elasticity effects" of significant dummy variables and continuous variables in this subsection. The elasticity effects and their standard deviations are presented in Table 6. Note that, since calculation formulas and implications of dummy variables and continuous variables are different, they cannot be compared and should be described respectively (Chiou and Fu, 2013).

Specifically, among dummy variables, all those eleven S_{NO} have the higher positive elasticity effects (>100%) on vehicle collisions compared to V_{type} and VL_{target}. It confirms that the position of vehicle has the significant effect on the higher probability of collision and all the eleven S_{NO} are key factors for more severe conflicts. Moreover, V_{type} (bus) and VL_{final} (Lane2) have positive elasticity effects which are 74.24% and 32.94% respectively. VL_{final} (Lane3) and VL_{final} (Lane4) have negative elasticity effects on vehicle collisions whose absolute values are less than that of V_{type} (bus). It indicates that the effect on the collision probability of vehicle type (bus) is higher than that of final toll collection lanes.

The elasticity effects of continuous variables are relatively less than those of dummy variables because of their different formulas. As shown in Table 6, the average speed of each vehicle in the total diverging area (V_v) has a largest negative elasticity effect (-4.43%) on the collision probability, suggesting that it is the most important factor contributing to vehicle collisions. This finding is expected since the TTC of vehicle is calculated from the speed of it directly. In addition, continuous variables of average traffic volume of diverging area segment (FVO) and average speed of surrounding vehicles (F_v) can also be regarded as a key factor contributing to the collision probability, due to the value of elasticity effects of them are 1.06% and -0.94%, respectively which are higher than other variables.

5. Conclusions

This study investigated the vehicle collision risk in the entire diverging area of traditional mainline toll plaza (TMTP). For the toll plaza up stream diverging area, there are significant multi-angle conflicts between vehicles due to the different vehicle collection types (MTC vehicle and ETC vehicle), various target collection lanes, changing width of road, and lack of lane marking. This study defined the toll plaza diverging area and extracted vehicle trajectory data from video using an automated analysis system. According to the characteristics of vehicle trajectory data, an extended TTC was proposed to evaluate the vehicle collision risk in the toll plaza diverging area. Subsequently, the different effects on vehicle collision risk of vehicles with different vehicle collection types, target lanes and locations were compared. Moreover, the random parameters logistic model was developed to investigate the relation between collision risk of diverging vehicles and various traffic parameters and elasticity effects were estimated to evaluate the magnitude of the effects of parameters on the vehicle collision risk. The major conclusions are as follow:

- Generally, ETC vehicles have higher collision risks than MTC vehicles in the toll plaza diverging area, Which is supported by the comparisons of the proportion of dangerous sample, the average TTC and the average dangerous time of MTC and ETC vehicles. However, when vehicles were classified into four groups according to the collection types and target lanes, it can be found that vehicles passing through MTC lanes which are located near the ETC lanes (Target Lane 2) are most dangerous.
- The effects of diverging area segments on vehicle collision risk of vehicles (Groups 1, 2 and 3: ETC-Target Lane1, MTC-Target Lane2, MTC-Target Lane3) have a rising trend among the entire diverging area. A vehicle could get more dangerous when it is closer to toll collection lanes. However, MTC vehicles passing by Target Lane 4 (Group 4) are more dangerous at the beginning of the diverging area.
- The logistic modeling results indicated that the effects of bus on vehicle collision risk is higher than that of car. The target toll collection lanes and diverging area segments have significant

Table 5
Modeling results of Random parameters model and Random effect model.

Variable	Description	Random parameters model		Random effect model	
		Estimate	Standard Error	Estimate	Standard Error
Intercept		1.70**	0.35	1.12**	0.65
Standard deviation of parameter		0.03**	0.01		
V_{type} (bus VS car)	Vehicle types	0.84**	0.29	0.76**	0.29
Standard deviation of parameter		0.17**	0.16		
V_{type} (truck VS car)		−0.07	0.29	0.05	0.29
Standard deviation of parameter		0.37	0.24		
VL_{target} (lane2 VS lane1)	Vehicle target toll collection lanes when it exits the toll plaza diverging area	0.24**	0.11	0.16*	0.11
VL_{target} (lane3 VS lane1)		−0.40**	0.13	−0.46**	0.12
VL_{target} (lane4 VS lane1)		−0.61**	0.20	−0.61**	0.21
V_v	Vehicle average speed in the total diverging area	−0.37**	0.02	−0.36**	0.04
Standard deviation of parameter		0.04**	0.01		
VDE_{max}	The maximum vehicle deceleration in the total diverging area (positive number)	0.02**	0.01	0.02**	0.01
S_{NO} (area2 VS area1)	Diverging area segments number	2.62**	0.27	2.89**	0.30
S_{NO} (area3 VS area1)		2.64**	0.27	2.93**	0.30
S_{NO} (area4 VS area1)		2.68**	0.28	2.96**	0.30
S_{NO} (area5 VS area1)		2.77**	0.02	3.05**	0.02
S_{NO} (area6 VS area1)		2.77**	0.27	3.05**	0.30
S_{NO} (area7 VS area1)		2.78**	0.26	3.05**	0.29
S_{NO} (area8 VS area1)		2.84**	0.27	3.11**	0.29
S_{NO} (area9 VS area1)		2.82**	0.26	3.10**	0.27
S_{NO} (area10 VS area1)		2.73**	0.25	2.99**	0.26
S_{NO} (area11 VS area1)		3.31**	0.24	3.58**	0.24
S_{NO} (area12 VS area1)		3.52**	0.21	3.82**	0.21
FVO	The average traffic volume of the area segment during the entry and exit period of vehicle i	0.0003**	<.0001	0.0003**	<.0001
$FMIX_{MTCETC}$	The mix measure of MTC and ETC vehicles in the area segment during the entry and exit period of vehicle i	0.18**	0.08	0.15*	0.08
Standard deviation of parameter		0.05**	0.03		
F_v	The vehicle average speed of total vehicles in the area segment during the entry and exit period of vehicle i	−0.08**	0.01	−0.07**	0.02
Standard deviation of parameter		0.06**	<.0001		
F_{vstd}	The standard deviation of total vehicles' speed in the area segment during the entry and exit period of vehicle i	0.08**	0.01	0.09**	0.01
Standard deviation of parameter		0.03**	0.02		
FDE	The average vehicle deceleration of total vehicles in the area segment during the entry and exit period of vehicle i	−0.19**	0.04	−0.18**	0.04
FDE_{std}	The standard deviation of total vehicles' deceleration in the area diverging segment during the entry and exit period of vehicle i	0.18**	0.04	0.18**	0.03
Random effect				0.68**	0.05
DIC	Deviance Information Criterion	11797.9		11887.1	
AUC	The area under Receiver Operating Characteristic (ROC)	0.7892		0.7804	

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

Table 6
Elasticity effects for of the random parameters model.

Dummy Variable	Mean (%)	S.D. (%)	Continuous Variables	Mean (%)	S.D. (%)
V_{type} (bus VS car)	74.24	36.12	V_v	−4.43	1.81
VL_{target} (lane2 VS lane1)	32.94	28.34	VDE_{max}	0.07	0.06
VL_{target} (lane3 VS lane1)	−23.36	16.15	FVO	1.06	0.53
VL_{target} (lane4 VS lane1)	−32.38	14.32	$FMIX_{MTCETC}$	0.04	0.06
S_{NO} (area2 VS area1)	123.31	335.42	F_v	−0.94	0.50
S_{NO} (area3 VS area1)	127.97	343.16	F_{vstd}	0.09	0.16
S_{NO} (area4 VS area1)	133.35	351.95	FDE	0.12	0.10
S_{NO} (area5 VS area1)	148.02	374.89	FDE_{std}	0.06	0.07
S_{NO} (area6 VS area1)	147.53	374.28			
S_{NO} (area7 VS area1)	148.30	375.15			
S_{NO} (area8 VS area1)	157.85	390.07			
S_{NO} (area9 VS area1)	154.02	382.48			
S_{NO} (area10 VS area1)	134.39	50.25			
S_{NO} (area11 VS area1)	245.52	533.38			
S_{NO} (area12 VS area1)	283.39	593.70			

relationships with the vehicle collision risk, which are consistent with the comparison results in Section 4.1 and 4.2. For each vehicle, the change of speed has a positive effect on the vehicle collision risk. There would be lower vehicle collision risk if the vehicle has higher average speed. Interestingly, vehicles would be more in danger if they are surrounded by heavy traffic (higher traffic volume or lower average deceleration of surrounding vehicles). The result also confirmed the mix of MTC and ETC vehicles has the significant effect on the safety of vehicles in the toll plaza diverging area.

The results in this paper contributed to verifying the higher collision risk in traditional toll plaza diverging area, and provided helpful information to highway safety improvement, such as applying Variable Speed Limits (VSL) and Dynamic Message Signs (DMS). Better and more innovative signage and pavement marking are needed. It is noteworthy that the Ministry of Transport in China has noticed the significant shortcomings of toll plazas and started to implement new measures to decrease the traditional mainline toll plazas since May 2018. Therefore, this study can provide theoretical supports to their countermeasures.

The authors recognize that much can be further investigated. In this

paper, only one typical toll plaza was analyzed. There may be differences between different designs of toll plazas. Therefore, it is recommended to take into account the number of MTC/ETC lanes, ratio of MTC and ETC lanes, and design of diverging area in the future researches. Second, the spatial correlations should be considered in the future study (Guo et al., 2018b; Zeng and Huang, 2014a, 2014b). On the other hand, the behavior of the individual driver should be highly correlated with the vehicle conflicts. Driving simulation experiments could be designed to validate various assumptions of drivers' behavior. Hence, the diverging behavior should be also considered for future research. Moreover, although this study used an extended TTC in the more general case of two-dimensional movement, the acceleration or deceleration and the severity of conflicts should be investigated in the future research. It is an inevitable to replace the MTC lanes with ETC lanes once a threshold of ETC penetration is achieved, as well as the developing Connected Vehicles' systems (Yue et al., 2018). The extended study should be conducted to investigate the effects of these ideas on vehicle collision risk and would be very meaningful. Validation of our models using crashes could also be an extension to this research.

Acknowledgements

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