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Research Article

Modeling Lane-Changing Behavior in Freeway Off-Ramp Areas from the Shanghai Naturalistic Driving Study

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The objective of this study is to investigate lane-changing characteristics in freeway off-ramp areas using Shanghai Naturalistic Driving Study (SH-NDS) data, considering a four-lane freeway stretch in various traffic conditions. In SH-NDS, the behavior of drivers is observed unobtrusively in a natural setting for a long period of time. We identified 433 lane-changing events with valid time series data from the whole dataset. Based on the logit model developed to analyze the choice of target lanes, a likelihood analysis of lane-changing behavior was graphed with respect to three traffic conditions: free flow, medium flow, and heavy flow. The results suggested that lane-changing behavior of exiting vehicles is the consequence of the balance between route plan (mandatory incentive) and expectation to improve driving condition (discretionary incentive). In higher traffic density, the latter seems to play a significant role. Furthermore, we found that lane-change from the slow lane to the fast lane would lead to higher speed variance value, which indicates a higher crash risk. The findings contribute to a better understanding on drivers' natural driving behavior in freeway off-ramp areas and can provide important insight into road network design and safety management strategies.

1. Introduction

Innovative technologies and traffic data sources provide great potential to extend advanced strategies and methods in road safety research. Advances in traffic safety modeling and analysis will play an important role in reducing road crashes and improving traffic operations. Lane-changing's adverse impact on traffic safety has been investigated and confirmed. Recent studies in traffic management have shown that lane-changing maneuvers are a major source of traffic disturbance on a multilane freeway [1]. Such maneuvers are also critical to road safety as 40% of freeway accidents happened in ramp areas, particularly in off-ramp sections [2]. A better understanding of lane-change events can also improve design of the human-machine interface in driving assistance systems.

Up to now, lane-changing characteristics and influencing factors in urban roads or freeways have been studied from the perspectives of driver behavior [3] and road and traffic conditions [4, 5]. In these studies, lane-changes can be classified as either mandatory or discretionary according to

driving incentives [6]. Generally traffic outflows do mandatory lane-changing (e.g., off-ramp or to avoid a block), while through traffic conduct discretionary lane-changing when drivers perceive that driving conditions in the target lane are better. So far there has been little research on the modeling of integrated mandatory and discretionary lane-changing strategies in freeway off-ramp areas.

Traffic on the fast lane must change to the shoulder lane before exiting a ramp on a freeway. Usually mandatory lane-changing to the shoulder lane is performed by the departure vehicles far enough before the off-ramp area. However, in actual traffic conditions, queue-jumping behavior occurs frequently when approaching an off-ramp and significantly affects traffic capacity and stability, which is neglected in most simulation programs. Furthermore, trade-offs between mandatory and discretionary incentives are limited. For example, when considering a mandatory lane-changing to exit a ramp, a driver may decide to overtake a heavy vehicle in front first (e.g., executing a discretionary lane-change first). Advances in data collection technologies, (e.g., the naturalistic driving system), giving access to high-resolution vehicular

data, provide an opportunity for us to fully understand the highly complex lane-changing procedure, particularly the trade-off decisions. Thus, it is valuable to conduct a comprehensively empirical study on lane-changing decision-making in freeway off-ramp areas.

The major lane-changing modeling methods consist of two distinct forms: lane-change decision model and lane-change influence model. For lane-changing decisions, Gipps introduced the original lane-changing model on urban roads which considered traffic signals, obstructions, and heavy vehicles [7], then several refined models based on Gipps were developed and extended to freeways [8, 9]. Ahmed et al. [10] employed random utility theory in lane-changing behavior modeling and a lane-changing choice was defined as a sequence of three steps: decision to consider a lane-change, choice of left or right lane, and search for an acceptable gap to execute the decision. Ahmed [11] extended the mandatory LC model to accommodate congested traffic, where forced merging behavior frequently occurs because of lacking of normally acceptable gaps. Toledo [12] developed a discrete choice framework to model integrated lane-changes and estimated the parameters. Other analysis methods of lane-changing behavior include risk-based models [13], as well as intelligent algorithms such as artificial neural networks [14] and fuzzy inference [15]. For example, Balal et al. [16] applied a fuzzy inference system to model a driver's binary decision to or not to execute a discretionary freeway lane-change. Research on the lane-changing behavior indicates that slower preceding vehicles would in many situations tempt the following drivers to consider overtaking, and 95% of drivers would choose to do lane-changing only if the rear spacing on the target lane is bigger than 15 meters and speeds are higher than the following vehicles on the target lane [17, 18]. Zheng [19] categorizes the major LC models in the literature into two groups: models that aim to capture the LC decision-making process and models that aim to quantify LC's impact on traffic.

Under the condition of dense traffic, a vehicle attempting a lane-change needs cooperation from at least one following vehicle in the target lane. Hidas [9] developed a cooperative lane-changing model based on a "driver courtesy" concept. By comprehensively reviewing previous works, Kesting et al. [20] proposed the model MOBIL (Minimizing Overall Braking Induced by Lane-changes) to address cooperative lane-changing of intelligent vehicles. Based on MOBIL, other researchers further studied intelligent lane-changing models [19]. On the empirical side, the studies of lane-changing behavior were far less extensive than those of longitudinal behavior (such as car following) due to the lack of comprehensive vehicle trajectory data. The emergence of connected vehicle technology offers some great opportunities.

Previous studies rely on theoretical calculation, traffic simulation, or driving simulator and field experiment to collect lane-changing behavior data. To overcome the restriction of driving simulation and field experiment such as short test horizon and limited controlled settings [21], the 100-car Naturalistic Driving Study (NDS) was the first large-scale NDS conducted in the US [22, 23], followed by the 60-Taxi NDS in

Japan [24]. The UDRIVE Naturalistic Driving Study was conducted from 2012 to 2016 in seven countries in Europe [25]. Naturalistic Driving Study, undertaken in natural conditions (no interference, no appearance of researchers, and during daily driving) [26, 27], provides the opportunity to observe the actual driving process with an unobtrusive high-precision data acquisition system. In comparison to the intensive efforts on driver behavior and microsimulation, lane-changing modeling using naturalistic driving data is still a relatively undeveloped area. Frequent and substantial lane-changes based on individual decisions and preferences can certainly affect traffic flow and road safety. Improper lane-changing has been identified as a main source of congestion and collisions [28]. It is a challenging task to fully understand the mechanism for lane-changes at freeway exits and it requires data of heterogeneous traffic conditions with varying degrees of driver behavior and perception.

However, real-time lane-changing characteristics cannot be obtained in most of the existing studies. Limited investigations have been made to identify hazardous lane-changing behavior; thus few of the models can be applied in real-time driving assistance systems. Lane-changing risk has been investigated as a surrogate safety measure to predict crash potentials in a mesoway. Typically, traffic data from loop detectors has been utilized to predict potential lane-changing related crashes and studies indicated that difference in occupancy of adjacent lanes was significantly associated with the crash potential [29]. Individual vehicular information was extracted for a surrogate index of crash risk and results showed the measure was effective in predicting traffic crash occurrence [30, 31]. Thus, naturalistic driving data provide the opportunity for researchers to fully investigate the safety factors in lane-changing.

The ongoing Shanghai Naturalistic Driving Study (SH-NDS) is a joint effort by Tongji University, General Motor China and Virginia Tech Transportation Institute. The objective of the SH-NDS is to investigate how drivers interact with vehicle, roadway, traffic conditions, and traffic control devices in China. Also SH-NDS offers the opportunity to investigate similarities and differences between Chinese drivers and drivers from other countries. Typically, a naturalistic observation vehicle was equipped with devices that continuously monitor various aspects of driving behavior, including information about vehicle movements (e.g., acceleration and deceleration, position on the road, and driving speed), about the driver (e.g., eye, head and hand movements), and about the direct environment (e.g., time headway, traffic density, road, and weather conditions).

The objective of this study is to investigate lane-changing characteristics in freeway off-ramp areas using SH-NDS data, considering a four-lane freeway stretch in various traffic conditions. This paper is organized as follows. Section 2 presents data collection and sampling; a description of the model structure is presented after that. The homogeneity and heterogeneity analysis as well as the safety assessment of lane-changing are discussed in Section 3. The last part concludes with remarks on the potential scope of future studies.

FIGURE 1: Four camera views in SH-NDS data acquisition system: forward view (left), in-cabin driver face view (upper left), instrument panel and steering wheel view (upper right), and rear view (bottom right).
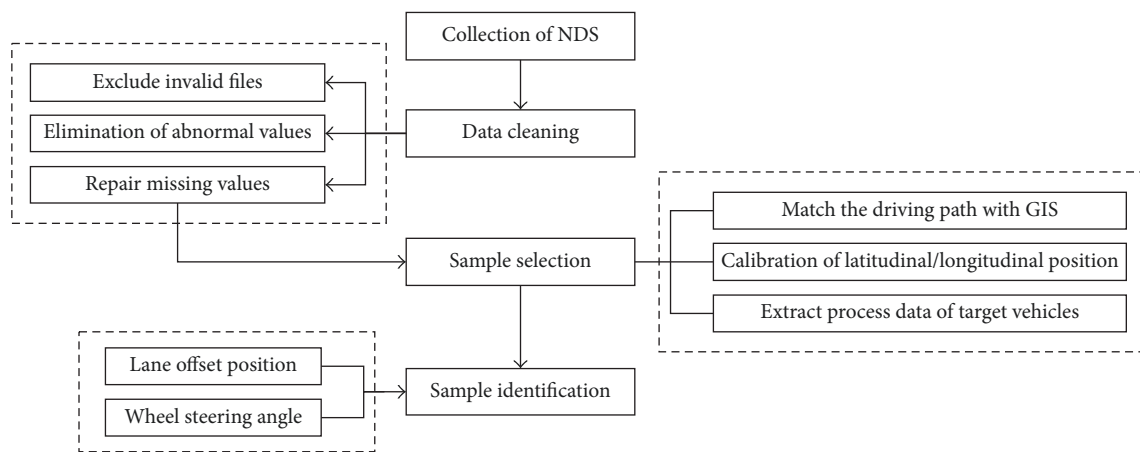

FIGURE 2: The procedure of data collection and extraction.

2. Method

2.1. Shanghai Naturalistic Driving Study Data. In this Shanghai naturalistic observation study, driving behavior was observed unobtrusively in a natural setting for a long period of time. A total of 60 drivers from the Shanghai metropolitan area have been involved since the end of 2012. They are between 35 and 50 years old, holding valid driving licenses, and with more than five years' driving experience. Participants were required to drive no less than 40 kilometers per day on average. Each participant drove the assigned vehicle, and every day the route was determined by themselves according to the needs of work and nonwork, without the presence of any researcher.

The instrumented vehicles were fitted with unobtrusive data acquisition systems consisting of GPS, high frequency video camera, triple axis accelerometer, Doppler radar, and lane offset system. The vehicle data acquisition system recorded data when the car was running and in-motion. The resultant dataset consisted of approximately 750,000 km of driving data (comprising more than 80,000 hours of video data). Each driver was assigned to one of five instrumented vehicles and drove the car for three months. After a participant completed her/his time in this study, a different driver

was assigned to the test car until the data collection process was completed for all participants.

Original naturalistic driving data are characterized by a large number of parameters. In this dataset, there are more than 10,000 CSV files which contain the information acquired from single trips. For the purpose of this study, lane-changing data in freeway off-ramp areas were chosen as (1) vehicle trajectory data and motion characteristics (e.g., speed, acceleration) in a selected freeway off-ramp segment; (2) neighboring traffic around the objective, which refers to surrounding vehicles' motion information within the scope of instrumented radar; (3) videos recorded by four in-vehicle cameras during the full process of ramp exiting, as shown in Figure 1, consisting of forward and rear views, steering wheel view, and driver's face.

The procedure of data collection and extraction is shown in Figure 2. The first task was data cleaning. In this paper, on the basis of a large number of field data analyses, an outliers monitoring method was proposed based on a self-learning Pauta criterion [32], which is the method of three times standard deviation to eliminate outliers. The outlier correction method was based on linear interpolation. The second step is to extract departure samples in the freeway
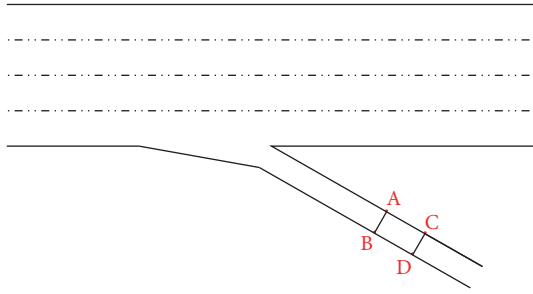
FIGURE 3: Schematic illustration of a study area.

FIGURE 4: An example of LO values in the dataset.

off-ramp sections. We consider a four-lane stretch of freeway. Figure 3 is an illustration of the study area. After matching the driving path to real road sections in GIS according to actual longitude and latitude data during the trips, we framed the range of the off-ramp in all the freeway exits in the dataset by calibrating the longitude and latitude position of points A to D. To ensure that all selected off-ramp events are under the same road conditions, we set up the criteria: a straight four-lane freeway stretch, distance of adjacent exits no less than 4 km, and being in fine weather conditions. Missing data due to limitations of the data collection were also accounted.

2.2. Identification of Lane-Changing Samples. Lane-changing behavior can be identified by one or more of the following episodes. (1) Driver initiates a steering input to change the direction of the vehicle. (2) The vehicle begins to move laterally relative to the lane. (3) The vehicle leaves the current lane at least temporarily [33]. To determine the initiation point of a lane-changing action, a search algorithm was adopted, in which lane offset position and steering wheel angle were applied as indexes to extract data associated with lane-change events. In addition, data analyzers manually inspected video of the triggered driving episodes and identified any valid lane-changes in qualified freeway off-ramp segments.

In general, the target lane of a lane-changing maneuver is the lane the driver perceives as best to be in, depending upon the prevalent driving conditions and her/his trip plan. In this study, the target lane is defined as the lane next to the vehicle. One of the lane offset position parameters is LO, which indicates the offset between the vehicle center line and the center line of the current lane, detected by the lane offset system. For example, as shown in Figure 4, a positive value of LO means the vehicle is offset to the right side of the current lane center, and a negative LO implies a left offset from the lane center line. Furthermore, once the test vehicle's center line crosses the current lane boundary (either the left or the right side), instrumented sensors automatically identify the new lane's center line; therefore the sign of LO value will turn to the opposite and appears as a sudden change. Thus single and serial lane-changing behavior can be differentiated according to the sudden change of the LO values. Steering wheel angle is taken as secondary index for verification. Totally 433 valid lane-changing samples were extracted from the dataset.
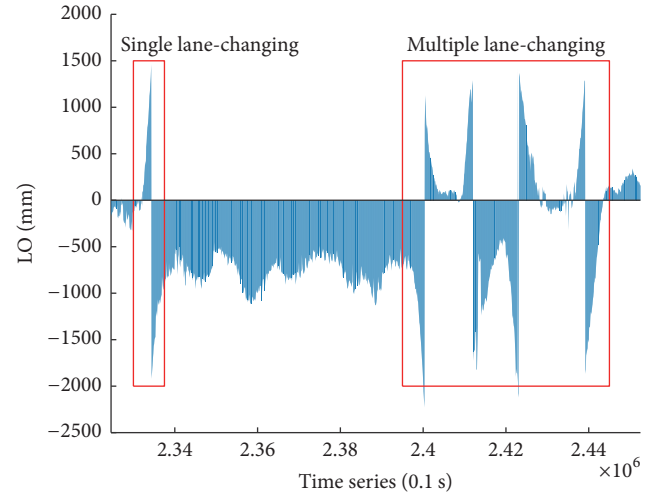
2.3. Preliminary Analysis of Lane-Changing Data. Figure 5 presents a typical scenario among the 433 samples. For convenience, the left-most lane is defined as the 1st lane and the right-most lane is defined as the 4th lane.

To explore the spatial distribution of lane-changing behavior in freeway off-ramp areas, we classified the 433 lane-changing events into three groups: changing from Lane 1 to Lane 2, from Lane 2 to Lane 3, and from Lane 3 to Lane 4. According to the initial position of a lane-change event, cumulative frequency can be plotted to show spatial attributes of lane-changes in different lanes (see Figure 6). The x-axis expresses the distance from an initial lane-changing position to the ramp. It can be shown that the number of lane-changes needed in order to exit the ramp is significantly correlated to the distance from initial lane-changing point to ramp. Based on the statistics of the samples, 85 percentile of lane-changes were made in the range, respectively, 2,300 m to 470 m in Lane 1, 1,800 m to 415 m in Lane 2, and 1,200 m to 290 m in Lane 3, as presented in Figure 7.

2.4. Modeling Lane-Changing Decisions. When test vehicles are driving on Lane 1 or Lane 4, drivers can only change in a single direction; hence, we finally selected 319 valid lane-changing actions starting from either Lane 2 or Lane 3. For the purpose of this study, variables influencing the target lane choice in freeway off-ramp areas are explained in Table 1.

Here, we followed Ahmed [11] and Toledo [12]'s LCD discrete choice framework. The target lane (TL) choice denotes the immediate lane of the test driver, depending on the driving route information and traffic environment. Due to the nature of the binary outcome, the target lane choice set includes two alternatives: either change to the left lane (LL) or the right lane (RL). To explain drivers' choice of these two alternatives, the concept of utility is used for measuring the satisfaction degree of changing to a target lane in specific traffic condition and driving route. The utility of LC for driver n is defined as in

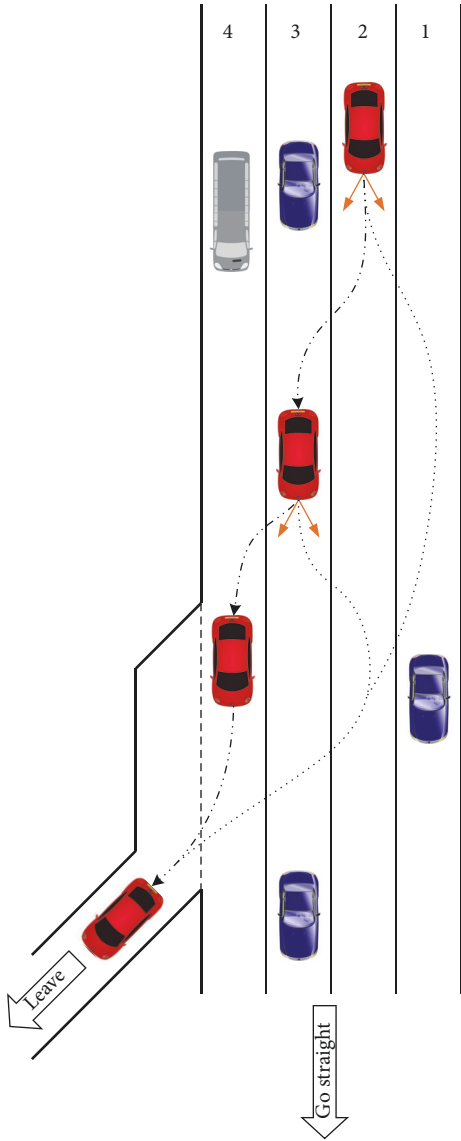$$U_n^i = \sum \beta^i X_n^i + v_n \alpha^i + \varepsilon_n^i, \tag{1}$$

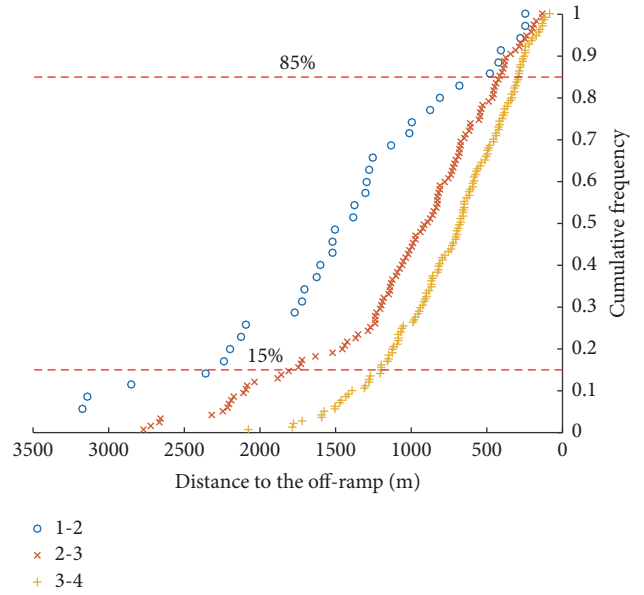FIGURE 5: The lane-changing process in freeway off-ramp areas.

FIGURE 6: Cumulative frequency graph of lane-changing longitudinal position on different lanes.
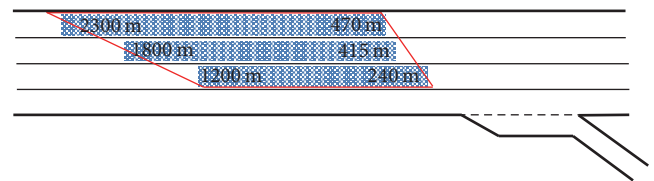
FIGURE 7: Range based on the 85 percentiles of lane-changing actions in each lane.

where U_n^i is the utility for driver n; $i \in \text{TL} = \{\text{LL}, \text{RL}\}$; X_n^i is a vector of explanatory variables; β^i is the corresponding coefficient to X_n^i; and ε_n^i is the random error term for a given individual, as well as across individuals. v_n is an individual specific random term that can represent observable/unobservable characteristics. α^i are the parameters of v_n. It may be noted that, due to the limitation of data collection, in estimation not all the α^i values can be identified.

Under the assumption that individual n chooses an alternative that maximizes his/her satisfaction, alternative i is chosen if and only if $U_{in} \geq U_{jn}$. Assuming the term ε_n^i follows an IID Gumbel distribution, the probability of individual n choosing alternative i can be expressed by a logit model as

$$P_n(\text{TL} = i) = \frac{\exp\left(V_n^i \mid v_n\right)}{\sum_{j \in \text{TL}} \exp\left(V_n^j \mid v_n\right)}, \qquad (2)$$

where $V_n^i \mid v_n$ are the conditional systematic utilities of the choice alternatives.

As mentioned in the previous section, lane-change utility functions depend on explanatory variables including driving route information, traffic environment, as well as driver characteristics. Due to the sampling criteria, the sample size of left lane-change (LL) choices is relatively small. Thus, LL was defined as alternative $Y = 1$. Although driver characteristics (e.g., driving style) naturally have significant impacts on various aspects of lane-changing decisions, data are not available in most field tests; nevertheless, their parameters can be captured by the individual specific term v_n [6, 12].

3. Results

3.1. Model Estimation. Several model diagnostics were used to check model goodness-of-fit and the statistical significance for each explanatory variable. A total of 20 variables were initially tested in the logit model and only 6 of them were found to be statistically significant. The final logit model was estimated with six explanatory variables as shown in Table 2. Whereas GT_l (Gap Time to the front vehicle on the left lane) was statistically significant at only the 90% confidence

TABLE 1: Potential factors contributing to the lane change.

Category	Factor	Data source
(1) Trip plan	Numbers of lane changes needed in order to exit the ramp	Determined by video of front view
	Relative distance to the off-ramp at the initial point of a lane-changing event	Calculated from the time series data
(2) Traffic environment	Density and speed of traffic in the lane, distribution of heavy vehicles, driving regulations, and so on	Video camera and Doppler radar
	Relative speed and gaps of the subject vehicle with respect to surrounding cars	We use Gap Time (GT) as index to reflect neighboring conditions GT $= D/\Delta v$
(3) Driver and vehicle characteristics	Demographic variables, physical conditions, driving experience	Questionnaire

TABLE 2: Model estimation results.

Variable	Descriptions	Definitions	Estimate	p value
*$\delta_{(\Delta CL)}$	The number of lane-changes required to be in the correct lane	$\delta_{(\Delta CL)} = 1$ or $\delta_{(\Delta CL)} = 2$	−1.986	<0.001
*S	The distance to the point where the driver needs to be off-ramp	unit: m	0.003	<0.001
*M_r	The front vehicle type on the right lane	heavy vehicles = 1; others = 0	1.802	<0.001
*GT_m	Gap Time to the front vehicle in current lane	$\dfrac{d_{nm}}{v_m - v_n}$	−0.094	<0.001
GT_l	Gap Time to the front vehicle on the left lane	$\dfrac{d_{nl}}{v_l - v_n}$	0.053	0.078
*GT_r	Gap Time to the front vehicle on the right lane	$\dfrac{d_{nr}}{v_r - v_n}$	−0.058	0.002
	Number of observations		319	
	log likelihood		−91.8	
	AIC		197.6	

Note. ∗ means that the variable is significant at 95% level. In China heavy vehicles cannot drive on fast lanes; thus only vehicle type on right-side was considered.

level, all other five independent variables were statistically significant at the 95% level with p value less than 0.05.

Driving route information variables are important in this model. The effect of the path selection is represented by $\delta_{(\Delta CL)}$ and S which capture the number of lane-changes required to be in the correct lane and the distance to the point where the driver needs to be in a specific position (an exit). In line with expectation the estimated coefficient of this $\delta_{(\Delta CL)}$ is negative, which means the utility of a LL choice decreases with the number of lane-changes the driver needs to perform in order to complete the desired path plan. In contrast, the utility can be magnified when the distance to the off-ramp increases, where the coefficient of S is positive.

Another group of variables capture surrounding driving conditions on drivers' lane-changing decisions. These consist of the relative speed and spacing with respect to the vehicles in front in the current lane, in the lanes to the left and to the right of the test vehicle. A positive and significant coefficient of M_r captures drivers' tendency to avoid following a heavy vehicle, as heavy vehicles generally drive at lower speed and require greater braking distance. Both significant and negative coefficients of GT_m and GT_r indicate that when traffic neighboring conditions in the current and right lanes meet drivers' expectation, the left lane is generally not their preference.

GT_l is only statistically significant at 90% level and has a positive estimated coefficient. A possible explanation can be correlated with generally better level-of-service in Lane 1 (fast lane) and Lane 2 on the left. Driver characteristics such as age and gender did not play a significant role in lane-changing in this experiment. Contrary to priori expectations, gap time to the lagging vehicle on an adjacent lane did not have a significant effect on lane-changes in the estimation. This may reflect the trade-offs between mandatory and discretionary considerations in an off-ramp segment. In order to check model prediction accuracy, a classification matrix was used to compare predicted outcomes to the observed outcomes. According to it, the model successfully predicted 86.21% of the lane-changing behavior in off-ramp areas, which confirms that the logit model gave a good fit to the dataset.

3.2. Analysis of the Target Lane-Changing Probability Distribution. Ramps have been regarded as a major source of conflicts and congestion on freeways [34]. Near off-ramp areas are potential locations for bottleneck formation when the fraction of vehicles attempting to change to the lanes that are connected to their destinations is high. A diverging operation involves two interactive traffic streams: the freeway traffic and the ramp traffic. Two aspects need to be taken into account while studying lane-changing at ramps: the incentive and safety. This part discusses both types of characteristics in our experiment.

As discussed, important explanatory variables affecting the target lane choices came from route plan and neighboring
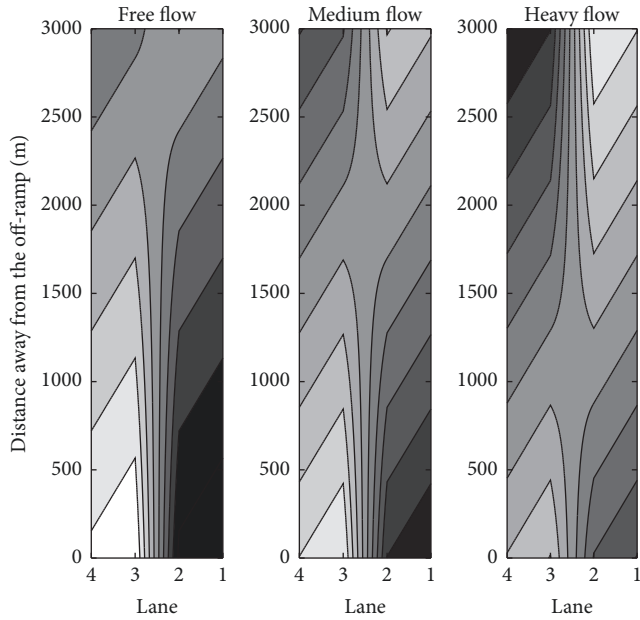
FIGURE 8: Lane-changing prob. sketch diagram in freeway off-ramp areas.

FIGURE 9: Spatial attributes with respect to cumulative frequency of lane-changes.

conditions. However, for a section of road, especially with a specific driving scenario (e.g., off-ramp), general traffic attributes, such as density and speed of traffic in the segment, also play a role for the lane-changes. Using time series DAS data, the information is available for estimation at discrete points on the test freeway segment. In a likelihood function of lane-changing behavior, a distribution of the distances from 3 km upstream to the off-ramp point was studied. For the sake of simplicity, we classified traffic into three levels: free flow, medium flow, and heavy flow.

We aim to quantify various traffic flows' impact on lane-changing. As shown in Figure 8, covering the three different traffic flow conditions, the lower right and top left corners with respect to the fast lane near the off-ramp and the shoulder lane far upstream of the off-ramp in a driving scenario have relatively low probability values. Correspondingly, the majority of mandatory lane-changes happened in the light gray area mainly along the three minor diagonals. In other words, we found the most likely lane-changing trajectory where drivers choose to change from lane 2 to lane 3 and at the last moment divert to lane 4 before arriving at the off-ramp, as displayed in Figure 5.

Our approach is innovative in the sense that the spatial and traffic attributes with respect to cumulative lane-changing rates can be measured in a quantitative and simultaneous manner. As the density is low, drivers start to carry out right lane-changing at earlier points. An explanation of this phenomenon can be that, in free flow, drivers are more likely to change lane to the right in advance without decreasing the feeling of comfort. Another interesting finding is that the more dense the traffic, the higher the wish to claim a position in the fast lane first. This implies that a driver postponing a response to a mandatory LC may have a higher propensity to perform discretionary LC. This can explain
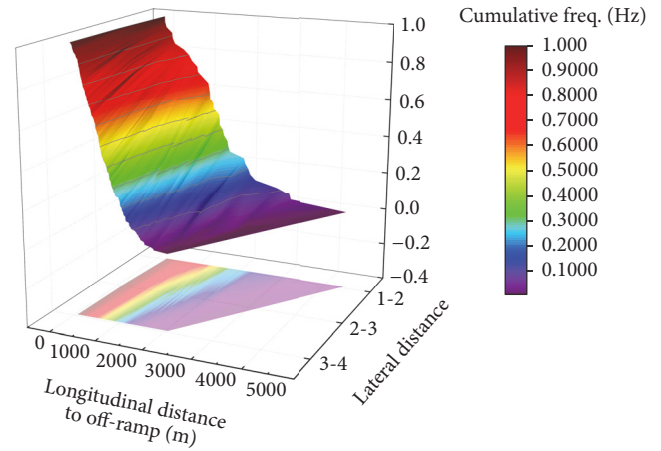
why, for an increasing density, a growth of lane-changes from the middle to the fast lane was found in the upstream stretch. The possible reason for these results is that when traffic density increases, vehicles at the upstream locations are more likely influenced by the pressure of surrounding vehicles and thus prefer to keep driving in the current lane or make a discretionary lane-change to the left. Hence they carry out right lane-changing actions for exiting only when approaching the off-ramp.

Furthermore, a lane-changing action will leave a gap in the original lane which may be used as gap to merge into by another vehicle. This case may happen more in higher density situations where vehicles are waiting for a gap and use this as soon as it becomes available. For some unobserved reason rather than the immediate traffic situations, a driver may decide on a particular lane-changing action [35], where there might be a trade-off between mandatory and discretionary. So if the fast lane for some reason is more attractive for the drivers, more vehicles change towards this fast lane. Even if it gets busier, the reason to go there can be still valid, and so drivers still move there in a dense situation. This theory is consistent with the results of the model estimates. Figure 9 displays spatial attributes (lateral and longitudinal distances to off-ramp) with respect to cumulative frequency of lane-changes.

3.3. Safety Assessment of Lane-Changing. Moreover, improper lane-changing action would result in potential safety hazards, such as rear-end crashes and sideswipe crashes. To put the lane-changing choice model into practice, safety assessment has been made to evaluate the potentially hazardous lane-changing behavior in this study.

There is a growing body of evidence to suggest a number of road safety benefits are associated with reduced speed variability between vehicles and reductions in 85th percentile speeds [36]. Specifically, increased speed variation may disturb homogenised traffic flow and increase the likelihood of conflict situations caused by human behavior [37].

Inspired by the findings, we applied the surrogate safety index Speed Variance (SV) of the following vehicle in the
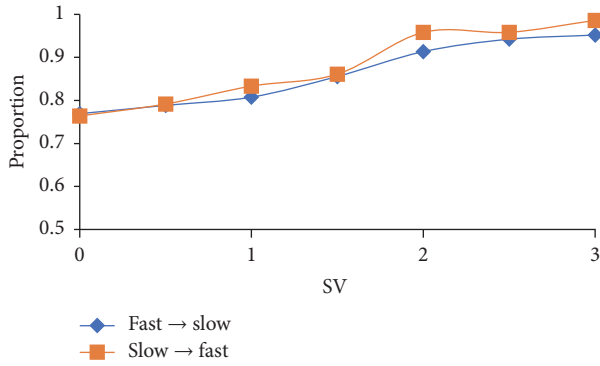
FIGURE 10: Cumulative frequency diagram of the speed variance of the lagging vehicle on the target lane.

target lane to assess the lane-changing behavior. The fundamental hypothesis concerning lane-changes is that any vehicle obeys a basic rule that lane-changing could be conducted only at least cost in speed reduction of neighboring vehicles; that is, a vehicle would change lane only if neighboring vehicles in the target lane would not have to slow down too much because of the lane-changing. Interestingly, in SH-NDS data, drivers are often cautious when they attempt to change lanes, especially under higher traffic density.

The SV value was calculated as

$$SV = \frac{V_t - V_0}{t}, \tag{3}$$

where V_t denotes the speed of the lagging vehicle in the target lane when the test vehicle starts to change lane; V_0 denotes the speed of the lagging vehicle in the target lane when the test vehicle has completed its action; t denotes the period of a lane-changing event. A cumulative frequency diagram of the SV values is displayed in Figure 10.

According to Figure 10, a large majority of lagging vehicles will not be impacted by the lane-changing events. In such circumstances, lane-change maneuvers are not supposed to interfere with the motion of neighboring vehicles on the adjacent lane. In contrast, under a more congested traffic and aggressive lane-changing scenario, the lagging vehicles have to decelerate to avoid a potential rear-end or sideswipe collision. In an extreme case, when the SV values are great enough, the driver of the lagging vehicle may feel a surge of anxiety. Figure 10 also indicates that lane-changes from the slow lane to the fast lane lead to slightly higher SV values. This result is consistent with the expectation that, when the vehicle's running speed is higher, a bigger spacing between the preceding vehicle and the lagging vehicle is required for a safe lane-change. The threshold values of SV were selected to identify the risky lane-changing actions based in the dataset. The 85 percentile value of the SV values can be utilized as the threshold in normal road conditions [38, 39]. Lane-changes from the slow lane to the fast lane (e.g., Lane 3 to Lane 2) relate to a slightly greater 85 percentile speed variation value than lane-changes from the fast lane to the slow lane (e.g., lane 2 to lane 3) (1.324 versus 1.297). This result is consistent with the expectation and with other related

works. A quantitative analysis of the safety assessment of lane-changes can contribute to the design of driving assistance systems. Once the improper lane-changing behavior has been identified, drivers can be alerted to the potential crash risk by in-vehicle driving assistance devices.

4. Conclusions

Studies of lane-changing behavior have been far less extensive than those of longitudinal driving behavior due to the lack of comprehensive vehicle trajectory data. For example, for the existing LC decision models, only a few have identified factors and developed lane-changing rules based on video evidence. Naturalistic driving study provides an opportunity to understand how drivers naturally interact with vehicle, roadway, and traffic environments. Naturalistic driving data have made it both technically and economically feasible to review kinematic information and driving behavior in natural surroundings on a large scale, through unobtrusive data gathering equipment and without experimental control.

Researchers have shown that lane-change maneuvers are primarily responsible for most of the traffic perturbations on multilane freeways. Therefore better understanding of lane-changing maneuvers is important in traffic studies, but this problem has not been satisfactorily investigated yet. In particular, in most off-ramp studies, lane-changes were considered as mandatory where the driver must leave the current lane. However, according to the data set of our naturalistic driving experiment and the analysis of this study, such classification of off-ramp lane-changing behavior seems to ignore trade-offs between mandatory and discretionary incentives. Applying a rigid lane-changing behavior model may result in unrealistic traffic flow characteristics. Only limited empirical studies have been done to accurately estimate the parameters of lane-changing models.

This study employed lane offset position and steering wheel angle as indexes to extract lane-changing samples in freeway off-ramp areas. Illustrated by the one-way four-lane freeway stretch, a logit model was developed to model the choice of target lanes. Parameters were estimated using vehicle trajectory data and individual characteristics. Estimations show that drivers' lane selection is impacted both by trip path variables and neighborhood traffic conditions. A likelihood analysis of lane-changing actions was graphed with respect to free flow, medium flow, and heavy flow.

The results suggest that lane-changing behavior of exiting vehicles is the consequence of the balance between route plan (mandatory incentive) and expectation to improve driving condition (discretionary incentive). In higher traffic density, the latter seems to play a significant role. The findings reveal the mechanism of lane-changing behavior near an off-ramp, which indicate the influencing factors as well as drivers' preferences in different traffic conditions. These can help improve driveway management in off-ramp areas and provide a reference for layout of guide signs. Therefore, traffic practitioners can take appropriate action, such as average speed enforcement and managed lane strategy, to make traffic smoother.

Near off-ramp sections, a lane-changing event may cause a harsh deceleration by the lagging vehicle and then may disrupt traffic and increase crashes and collisions. We applied the speed variance of the following vehicle in the target lane as a safety surrogate index. Moreover, lane-changing from slow lane to the fast lane would lead to a higher SV value. A series of thresholds are listed for real-time lane-changing safety assessment. It provides an opportunity to avoid potential rear-end or sideswipe crash. Further work is being conducted to study urban roadway stretches where the distance between ramps is shorter. For a more realistic and robust model, heterogeneity of vehicle composition in the roadway and geometry-specific effects should also be considered. Finally future studies need to also consider squeezed lane-changing behavior and driver negotiation with different off-ramps.

This is one of the first comprehensive studies using the Shanghai Naturalistic Driving Study data. The findings contribute to a better understanding of drivers' natural driving behavior in freeway off-ramp. This paper provides important insights into road network design and transportation safety strategies.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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