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Modeling and Analysis of Driving Decision at Traffic Bottlenecks

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ABSTRACT

The driving behaviors at bottlenecks are complex, and complex driving behaviors lead to the phenomenon of lateral separation which makes traffic flow more unstable. Therefore, it is necessary to build an appropriate decision model to describe the driving behaviors at bottlenecks and improve the accuracy of the microscope traffic simulation. This paper takes the lateral separation into consideration and analyzes the driving behaviors at traffic bottlenecks. To improve the model's interpretability, the decision model integrates the discrete choice model and the hidden Markov model (HMM). And there are two stages in the decision-making process: driving behavior choice and feasibility analysis. Then the analysis of variance is introduced to screen the involved influencing factors. Moreover, this model is verified with the vehicle trajectory data and result shows that the proposed model not only has a good performance but also can explain why different behavior is undertaken.

Keywords: *Transportation Engineering, Traffic Bottleneck, Driving Behavior, Hidden Markov Model, Discrete Choice Model, Factor Analysis*

INTRODUCTION

With the rapid development of the economy, urban traffic congestion problem has become acute, not only makes the travel time increases significantly but also leads to severe air pollution. As we all known the congestion always occurs at the traffic bottlenecks. At the bottlenecks, drivers have the desire to pass it as soon as possible, so they are more likely to change the lane frequently or don't drive obey the lane. As a result, the driving behavior is disordered and lateral separation exists widely especially in developing countries.

Fig.1 shows the distribution of vehicular lateral position at bottlenecks. The vehicle trajectory data was collected in Guangzhou, China. On the whole, the vehicular lateral position within the current lanes obey normal distribution which is consistent with Gunay's (2007)work. However, in the middle lane and shoulder lane, the lateral separation exists widely and the frequency is more evenly. And there is a bus stop nearby, so frequent lateral movements occur.

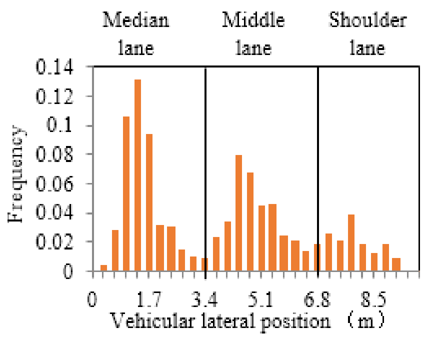


Figure1. *Distribution of the lateral distance between the vehicles and road centerline*

Because of the lateral separation phenomenon, the lateral distance between two vehicles can be very small or very large. As a result, the large lateral distance between two vehicles can stimulate the following vehicle to drive in the gap. It's common to see that there are multiple vehicles can travel in parallel at bottlenecks, especially in many developing countries.

As the Figure 2 shows, there are three vehicles drive in two lanes. However, this behavior can't be explicitly defined as the car-following behavior or lane-changing behavior. Furthermore, the complex driving behavior is often accompanied by the continuous acceleration and deceleration process and the mutation of the vehicle's position, which can make the traffic to be more chaotic. And maybe one vehicle's disordered behavior can lead to the serious traffic congestion, which can seriously decrease the capacity and service level of the road.

Figure2. *The disordered behaviors at bottleneck*

Therefore, it's necessary to build a driving behavior decision model at bottlenecks to make the traffic simulation more practical and reliability. And it also can provide reference and a basis for the formulation of traffic policies and the planning of the transport infrastructure.

This paper starts with the background introduction to address the complex behavior at bottlenecks and its impact. The review of the decision model is in Section 2. The hybrid driving behavior decision model is proposed in Section 3. And the parameter estimation and discussion are presented in Section 4. We close the paper with conclusions in Section 5.

LITERATURE REVIEW

As for the classic lane-changing decision models such as Gipps-type models(Gipps,1981; Gipps,1986; Yang and Koutsopoulos,1996), CA models(Daganzo,2004), utility theory based (Ahmed ,1999) models has been developed a lot. Besides the classic models, the Markov process is another widely used method for modeling lane-changing behavior. At the beginning, the Markov based models aimed to reproduce lane-changing frequency Worrall et al. (1970) developed a stochastic lane-changing model based on homogeneous Markov chain and used naturalistic data collected in Chicago to calibrate the model. Then Singh and Li (2012) use Markov characteristic to get the probability of lane-changing behavior.

On the basis of previous research, Hou (2013) combining the HMM model with PCA. And Cao (2014) proposed a modeling method based on the Multi-Hidden Markov model(M-HMM). And Peng(2015) proposed a lane-changing behavior model combines neural network model and HMM. Then, Li et al. (2016) proposed a novel lane-changing intention recognition model combining the HMM and Bayesian filtering; the proposed models use an extra filter to improve the recognition performance compared with the HMM-only or SVM-only methods.

It's easy to find that the HMMs are a naturally suitable tool to model lane-changing behavior because they can model the stochastic nature of the driving behavior and support the recognition of temporal data patterns. What's more HMM model can be well integrated with other models, it's easy to expand. Nonetheless the above models can only tell the lane-changing frequency, but cannot explain the decision process: why or why not LC occurs. This limitation is overcome by Toledo and Katz(2009).

However, all the above models are focus on the freeway, while the driving behavior is more complex at bottlenecks, and lateral separation makes traffic flow more unstable. The models didn't take the disordered behavior into account, just considered changing lane or not. So this paper will focus on the disorder behavior at bottlenecks.

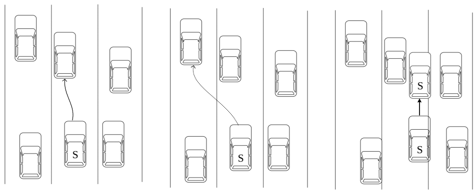
HYBRID DRIVING DECISION MODEL

Categories of Driving Behavior

Firstly, the categories of vehicular behavior at traffic bottlenecks should be discussed. As the introduction mentioned, because of the lateral separation characteristic, the vehicle can drive in the gap between the preceding vehicle and the lateral preceding vehicle. In this paper, this behavior is called gap-following behavior, because it's following target is the gap between two preceding vehicles. As a consequence, the driving behaviors are classified into 3 kinds according to current driving conditions. There are car-following(CF) behavior, lane-changing(LC) behavior, and gap-following(GF) behavior, as shown in Figure 3.

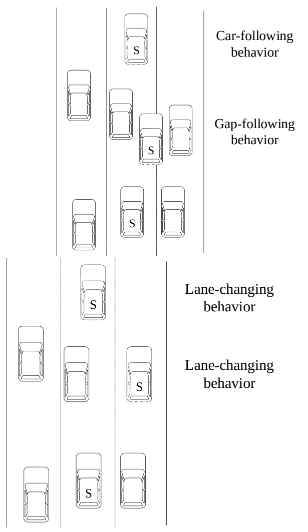
What's more, it's worth mentioning that driving is a dynamic and continuous process, and at each time step the process is divided into two stages: decision making and execution. This paper will focus on this decision making process. As for the execution, take He's study (2013) for reference. The concept of following target is introduced, the vehicle will follow different targets to execute the decision. Therefore, different decisions have different following targets, the following targets of car-following behavior, lane-changing behavior and gap following behavior are the lateral lead vehicle, the current lead vehicle, and the gap between the lead vehicle and the lateral lead vehicle respectively.

Recently the overtaking behavior has been discussed a lot (Chandra and Shukla, 2012), while an overtaking behavior can be decomposed into a gap-following behavior and a car-following behavior or continuous lane-changing behavior, as shown in Figure 4. So the three behaviors proposed in this paper are regarded as the basic components of the driving behavior.



(a) Car-following (b)lane-changing (c)Gap-following

Figure3. *Schematic diagram of driving behavior*



(a)gap-following behavior and car-following behavior (b) continuous lane-changing behavior

Figure4. *Overtaking behavior decomposition schematic diagram*

The HMM Structure of Model

A hidden Markov model (HMM) can be regarded as the dynamic Bayesian network. It has double stochastic characteristics, including a Markov chain and a general stochastic process. In this paper the driving behavior decision process has two stages: generation of the intention and feasibility analysis. The generation of the intention is corresponding to the Markov process and the feasibility analysis is corresponding to the general stochastic process.

Firstly, in generation of the intention stage, the Markov process is used to represent the transfer probability between the three driving intentions. At the same time, in order to improve the interpretability of the model, a discrete choice model is introduced to describe the probability transfer matrix between three states. And the driver will choose the best choice according to the desire and the surrounding driving environment. Then, the driver will consider the feasibility according to the gap acceptance model.

Figure 5 shows the structure of the model. In the first stage the arrows between the behavior represent the transition probability from one behavior to another at the next step. As shown in figure 5, at time t the decision is lane-changing, then at time $t+1$, the probability of different choice is dependent on the previous choice. In the second stage, the arrows between the intention and feasibility means the success probability of executing the decision.

Note that the intention means the action that the driver will consider. Then the driver will evaluate the feasibility to accept the intention or reject it. And if the driver rejects the lane-changing choice and gap-following choice at the second stage, the driver will choose car-following behavior. In other words, the car-following behavior is the timidest choice. Note that the two stages are affected by lots of factors, such as the neighboring vehicles. In the next sections the two submodels to capture these effects are presented in detail.

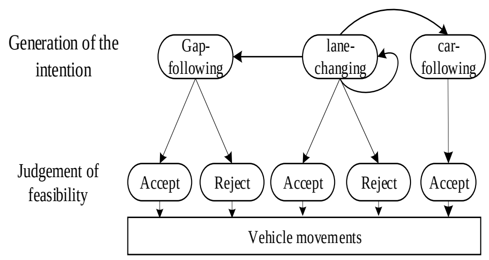


Figure5. *The structure of the model*

Intention: Behavior Choice Model

As we all known, the drivers expect to pass the bottlenecks as soon as possible, so the driver is assumed to select the best driving behavior. The utility model is suitable for evaluating the different choice. For the driver, the decision with highest utility is chosen. The utilities of different choices depend on the relationship between the subject vehicle and neighboring vehicles, such as the velocity differences, lateral distance, longitudinal distance and so on. What's more an individual-specific error term is introduced in the utility model to capture the unobserved characteristics of the driver. Therefore, the utility of choice i to driver n at time t is given by

$$U_{nt}^{i} = \beta^{i} X_{nt}^{i} + \rho\delta_{n,t-1}^{i} + \alpha^{i}\upsilon_{n} + \varepsilon_{nt}^{i} \quad (1)$$

And the involved parameters and meaning are shown as follows:

U_{nt}^{i} utility of the decision i to the driver n at time t, (i=lane-changing, car-following, gap-following);

$\beta^{i} X_{nt}^{i}$ explanatory variables and the corresponding parameters;

$\rho\delta_{n,t-1}^{i}$ dummy variable, if choice of time t is the same with time $t-1$, $\delta_{n,t-1}^{i}=1$ and 0 otherwise;

$\alpha^{i}\upsilon_{n}$ individual-specific error term, which obey normal distribution and the corresponding parameters

ε_{nt}^{i} random term, obey Gumbel distribution.

It is assumed that ε_{nt}^{i} obeys Gumbel distribution, the transition probability between different choice can be calculated by the follow equation,

$$P(B_{nt} = i \mid B_{n,t-1}, v_{n}) = \frac{\exp(\beta^{i} X_{nt}^{i} + \rho\delta_{n,t-1}^{i} \mid v_{n})}{\sum_{j \in J} \exp(\beta^{j} X_{nt}^{j} + \rho\delta_{n,t-1}^{j} \mid v_{n})} \quad (2)$$

Feasibility: Gap Acceptance Model

As for different intentions, different acceptable gaps should be considered separately. When driver's intention is lane-changing behavior, the lateral lead gap which means the longitudinal distance of the lateral preceding vehicle and the lateral lag gap which means the longitudinal distance of the lateral lag vehicle should meet the critical gap. As for the gap-following following behavior, the lateral gap which means the lateral distance between the preceding vehicle and lateral preceding vehicle and the lateral lag gap should meet the critical gap. Note that the success probability of car-following behavior is 1. And the general formula of the critical gaps is shown by equation (3).

$$CG_{nt}^{g} = \beta^{g} X_{nt}^{g} + \alpha^{g}\upsilon_{n} + \varepsilon_{nt}^{g} \quad (3)$$

Where,

CG_{nt}^{g} the critical gap to driver n at time t, $g \in \{lat\_lead, lat\_lag, lat\_gap\}$

$\beta^{g} X_{nt}^{g}$ explanatory variables and the corresponding parameters;

$\alpha^{g}\upsilon_{n}$ individual-specific error term, which obey normal distribution and corresponding parameters;

ε_{nt}^{g} random term, obey normal distribution.

The probability of lane-changing behavior and gap-following behavior are given by equation (4) and equation (5). And the $G_{nt}^{lat\_lead}$, $G_{nt}^{lat\_lag}$, $G_{nt}^{lat\_gap}$ are the actual distance correspondingly.

$$\begin{aligned} &P(gap-acceptance_{n,t}^{LC} \mid B_{nt} = LC, \upsilon_{n}) \\ &= P(G_{nt}^{lat\_lead} > CG_{nt}^{lat\_lead} \mid B_{nt} = LC, \upsilon_{n}) \\ &\cdot P(G_{nt}^{lat\_lag} > CG_{nt}^{lat\_lag} \mid B_{nt} = LC, \upsilon_{n}) \end{aligned} \quad (4)$$

$$\begin{aligned} &P(gap-acceptance_{n,t}^{GF} \mid B_{nt} = GF, \upsilon_{n}) \\ &= P(G_{nt}^{lat\_lag} > CG_{nt}^{lat\_lag} \mid B_{nt} = GF, \upsilon_{n}) \\ &\cdot P(G_{nt}^{lat\_gap} > CG_{nt}^{lat\_gap} \mid B_{nt} = GF, \upsilon_{n}) \end{aligned} \quad (5)$$

Assuming $\varepsilon_{nt}^{g} \sim N(0, \sigma_{g}^{2})$, and the conditional probability is given by equation(6).

$$\begin{aligned} &P(G_{nt}^{g} > CG_{nt}^{g} \mid B_{nt}, \upsilon_{n}) \\ &= P(G_{nt}^{g} - \beta^{g} X_{nt}^{g} - \alpha^{g}\upsilon_{n} - \varepsilon_{nt}^{g} > 0 \mid B_{nt}, \upsilon_{n}) \\ &= P(G_{nt}^{g} - \beta^{g} X_{nt}^{g} - \alpha^{g}\upsilon_{n} > \varepsilon_{nt}^{g} \mid B_{nt}, \upsilon_{n}) \\ &= \Phi\left(\frac{G_{nt}^{g} - \beta^{g} X_{nt}^{g} - \alpha^{g}\upsilon_{n}}{\sigma_{g}}\right) \end{aligned} \quad (6)$$

Likelihood function

As mentioned above, the two sub-models calculate the conditional probability, then the joint probability of the sequence of observation is given by

$$\begin{aligned} &P(I_{n} \mid v_{n}) \\ &= \prod_{t=1}^{T} \sum_{i} \sum_{j} P(B_{nt} = i, B_{n,t-1} = j, gap-acceptance_{n,t}^{i} \mid v_{n}) \\ &= \prod_{t=1}^{T} \sum_{i} \sum_{j} [P(B_{n,t-1} = j \mid v_{n}) \cdot P(B_{nt} = i \mid B_{n,t-1} = j, v_{n}) \\ &\quad \cdot P(gap-acceptance_{n,t}^{i} \mid B_{nt} = i, B_{n,t-1} = j, v_{n})] \\ &= \prod_{t=1}^{T} \sum_{i} \sum_{j} [P(B_{n,t-1} = j \mid v_{n}) \cdot P(B_{nt} = i \mid B_{n,t-1} = j, v_{n}) \\ &\quad \cdot P(gap-acceptance_{n,t}^{i} \mid B_{nt} = i, v_{n})] \end{aligned} \quad (7)$$

And the $P(gap-acceptance_{n,t}^{i} \mid B_{nt}, \upsilon_{n})$ and $P(B_{nt} = i \mid B_{n,t-1}, v_{n})$ can be calculated by equation (2) and equation (6) , the remaining part is can be calculated recursively as follow:

$$\begin{aligned} &P(B_{n,t} \mid v_{n}) \\ &= \sum_{i \in I} P(B_{n,t} = i \mid v_{n}) \\ &= \sum_{i \in I} \sum_{j \in J} P(B_{n,t} = i \mid B_{n,t-1} = j, v_{n}) \cdot P(B_{n,t-1} = j \mid v_{n}) \end{aligned} \quad (8)$$

The likelihood function and the log likelihood function is given by equation (9) and equation (10).

$$L_{n} = \int_{v_{n}} P(O_{n} \mid v_{n}) f(v_{n}) dv_{n} \quad (9)$$

$$L = \sum_{n=1}^{N} \ln(L_{n}) \quad (10)$$

where $f(v_n)$ is standard normal distribution.

Influencing factors

As above, the two sub-model is introduced, and the model can be estimated by collected data. However, researchers usually select the influencing factors according to the experience, and do not select important factors according to the actual data. Especially in this complex situation in which the driving behaviors are disorder, the involved influencing factors have their particularity. So it is necessary to screen the influencing factors.

The classic microscopic traffic flow model is based on the stimulus-response theory. It is generally believed that the driver's reaction (driving behavior) is caused by the stimulus (objective driving conditions). Therefore, this study believed that different stimuli are the reasons for drivers to make different decisions. If a factor has a significant impact on decision-making process, the factor of three different decisions should be significantly different. According to the idea, analysis of variance is introduced to screen the factors.

Therefore, the idea of screening factor is based on the theory of stimulus response, using variance analysis method. In this study, the surrounding vehicles that have impact on subject vehicles include the preceding vehicle, the lateral preceding vehicle and the lateral following vehicle, is shown in Figure 5.

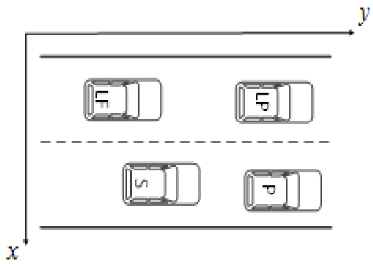


Figure5. *Relationship between the subject vehicle and the surrounding vehicles*

Therefore, there are 18 potential factors, the factors and its corresponding formula, as shown in Table 1.

Table1. *Potential influencing factors*

Symbol	Involved vehicles	Factors	Formula
ΔS^P	subject vehicle and preceding vehicle	Longitudinal distance	y^S -y^P
ΔX^P		Lateral distance	x^S -x^P
ΔV^P		Velocity difference	v^S -v^P
ΔS^{LP}	subject vehicle and lateral preceding vehicle	Longitudinal distance	y^S -y^{LP}
ΔX^{LP}		Lateral distance	$\|x^S$ -$x^{LP}\|$
ΔV^{LP}		Velocity difference	v^S -v^{LP}
ΔS^{LF}	subject vehicle and lateral following vehicle	Longitudinal distance	y^S -y^{LF}
ΔX^{LF}		Lateral distance	$\|x^S$ -$x^{LF}\|$
ΔV^{LF}		Velocity difference	v^S -v^{LF}
ΔS^{P-LP}	preceding vehicle and lateral preceding vehicle	Longitudinal distance	y^P -y^{LP}
ΔX^{P-LP}		Lateral distance	$\|x^P$ -$x^{LP}\|$
$\Delta V^{P\text{-}LP}$		Velocity difference	v^P -v^{LP}
ΔS^{P-LF}	lateral preceding vehicle and lateral following vehicle	Longitudinal distance	y^P -y^{LF}
ΔX^{P-LF}		Lateral distance	$\|x^P$ -$x^{LF}\|$
ΔV^{P-LF}		Velocity difference	v^S -v^{LF}
ΔS^{LP-LF}	preceding vehicle and lateral following vehicle	Longitudinal distance	y^{LP} -y^{LF}
ΔX^{LP-LF}		Lateral distance	x^{LP} -x^{LF}
ΔV^{LP-LF}		Velocity difference	v^{LP} -v^{LF}

Model Estimation

Data Collection

This paper focuses on the driving behavior at urban traffic bottlenecks, so this paper selects a three-lane section in Guangzhou as the experimental road, as shown in Figure 6.

According to the collected data, the traffic flow of the road is 1400pcu/h/ln. means the traffic of this road is heavy. What's more, there is a bus station near here. The behavior of the vehicle is affected by the bus enter or leave, and there is a serious lateral interference.

It is easy to lead to traffic congestion. As we all know, modeling the lane-changing behavior is more difficult than car-following behaviors because more vehicles are involved. So not only the subject vehicle's trajectory but also the neighboring vehicles' trajectories should be collected. And the video recognition technology is introduced to obtain the track of the vehicle.

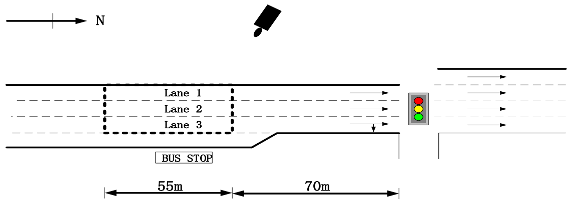


Figure6. *Schematic diagram of survey road*

The initial data include the car-ID and the corresponding sampling time, abscissa and ordinate values and the time step is 0.4s. In order to obtain the training data, the data process is shown in Figure 7.

Firstly, according to the trajectories of vehicles, the velocity can be calculated, and the neighboring vehicles can be found. Then the velocity differences and position relationship can be calculated respectively.

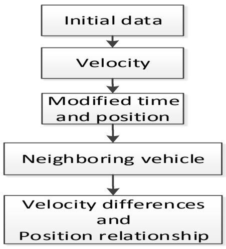


Figure7. *Data processing*

Factor

After normality test and variance homogeneity test of the sample data, variance analysis can be used to compare means of different factors under different decisions. In this paper, we choose the factor that p-value is less than or equal to 0.05. The factors that have significant differences under different decisions will have a greater impact on driving behavior. The means of factors under different behaviors and the result of multiple comparison is shown in table 2.

The results show that factor 1,2,3,5,6 have impact on the car-following behavior and lane-changing behavior. The factor 1,2,3,5 have impact on the car-following behavior and gap-following behavior. The factor 4,5 have impact on the lane-changing behavior and gap-following behavior.

It is found that the drivers do not only pay attention to the position relationship between subject vehicle and the surrounding vehicles, but also take the position relationship among the surrounding vehicles into consideration, such as the longitudinal distance between the preceding vehicle and the lateral preceding vehicle. Note that this kind of factor is less considered in the previous model.

Moreover, by comparing the means of the factors under different decisions, the reasons for the decision can be explained. For example, factor 4 is the lateral distance between the preceding vehicle and the lateral preceding vehicle. The average distance under the gap-following behavior is biggest, which means when the lateral distance is bigger the vehicle is more likely to following the lateral gap.

Table2. *Significant factors*

Significant factors	*Car-following*	*Lane-changing*	*Gap-following*	*P-value*	*Multcompare*
1. ΔS^{P} /m	10.59	5.38	5.56	5.09E-13	CF-LC CF-GF
2. ΔS^{P-LP} /m	6.12	-0.39	0.15	4.59E-10	CF-LC CF-GF
3. $\Delta S^{LP\text{-}LF}$ /m	7.27	12.05	10.13	0.04	CF-LC CF-GF
4. ΔX^{P-LP} /m	3.25	3.06	3.78	0.05	LC-GF

5. ΔV^{LP} / ms^{-1}	1.09	-2.66	0.18	1.80 E-3	CF-LC-GF
6. $\Delta V^{P\text{-}LP}$ / ms^{-1}	0.82	-2.65	-1.20	2.40 E-3	CF-LC

Estimation result

Using the collected data, the model estimation result is shown as follow. First it's the behavior choice model.

$$
\begin{aligned}
U_{nt}^{i} = \beta^{i} &+ (2.91\Delta S_{nt}^{P} + 3.47\Delta S_{nt}^{P-LP} - 1.37\Delta S_{nt}^{LP-LF} \\
&+ 2.83\Delta V_{nt}^{LP} + 4.01\Delta V_{nt}^{P-LP})\ \xi_{nt}^{i=CF} \\
&+ (-3.24\Delta S_{nt}^{P} - 1.72\Delta S_{nt}^{P-LP} + 2.15\Delta S_{nt}^{LP-LF} \\
&- 0.82\Delta X_{nt}^{P-LP} - 3.10\Delta V_{nt}^{LP} - 2.77\Delta V_{nt}^{P-LP})\ \xi_{nt}^{i=LC} \\
&+ (-3.56\Delta S_{nt}^{P} - 0.13\Delta S_{nt}^{P-LP} + 1.10\Delta S_{nt}^{LP-LF} \\
&+ 3.71\Delta X_{nt}^{P-LP} + 0.10\Delta V_{nt}^{LP})\ \xi_{nt}^{i=GF} \\
&+ 0.23\delta_{n,t-1}^{i} + 0.15v_{n} + \varepsilon_{nt}^{i}
\end{aligned}
\tag{9}
$$

By analyzing the parameters' symbols of corresponding factors, the reasons for drivers' choice can be explained. For example, as for the gap-following behavior, the parameter of the longitudinal distance between the subject vehicle and the preceding vehicle is negative, which means that the farther the distance, the smaller the utility is. And the longitudinal distance between the lateral preceding vehicle and the lateral following vehicle and the lateral distance between the preceding vehicle and the lateral preceding vehicle are positive, which means that the larger the distance, the driver is more likely to choose the gap-following behavior. The velocity difference between the subject vehicle and lateral preceding vehicle is positive, when the subject vehicle is faster than the lateral preceding vehicle, the driver is more expected to follow the gap between the two preceding vehicles.

Furthermore, the weight of the corresponding parameters can be discussed. It is found longitudinal or lateral distances between vehicles have a significant impact, which means that for drivers, the stimulus of space distance has great impact on the decision making.

Then the estimation result of critical gap is shown as follow,

$$
\begin{aligned}
CG_{nt}^{lat\_lead} &= 5.498 + 0.324\max(0,\ \Delta V_{nt}^{LP}) \\
&+ 0.099\upsilon_{n} + \varepsilon_{nt}^{lat\_lead}
\end{aligned}
\tag{10}
$$

For the lateral lead gap, when lateral preceding vehicle is faster, it is easier to change the lane.

$$
\begin{aligned}
CG_{nt}^{lat\_lag} &= 6.243 - 0.812\min(0, \Delta V_{nt}^{LF}) \\
&+ 0.48\upsilon_{n} + \varepsilon_{nt}^{lat\_lag}
\end{aligned}
\tag{11}
$$

For the lateral lag gap, when the lateral follow vehicle is slower, it is easier to change the lane or follow the gap between the two preceding vehicles.

$$
\begin{aligned}
CG_{nt}^{gap} &= 3.91 + 0.48\max(0, \Delta V_{nt}^{P}) + 0.61\max(0, \Delta V_{nt}^{LP}) \\
&+ 0.310\upsilon_{n} + \varepsilon_{nt}^{lat\_gap}
\end{aligned}
\tag{12}
$$

As for the lateral gap, when the subject vehicle faster than the two preceding vehicle, it's more difficult to follow the gap between the two preceding vehicles.

What's more, in this paper, two experiments were conducted. Besides the methodology that paper proposed, the basic HMM structure is also conducted. It's easy to find that when using the hybrid HMM structure, the precision and accuracy are increase.

Table3. *Experimental results*

		Hybrid HMM structure	**Basic HMM structure**
Precision	Car-following	87.51%	76.15%
	Lane-changing	82.62%	72.31%
	Gap-following	80.94%	71.54%
Accuracy		82.43%	75.54%

Conclusion

In this paper, the driving behavior decision at bottleneck is analyzed, and three basic driving decisions are put forward in consideration of the lateral separation phenomenon. The model framework is established by integrating HMM and discrete choice model, and analysis of variance is introduced to screen the factors. Finally, the model is verified by collected data, and the conclusions are as follows:

(1) Using analysis of variance to screen the factors, it is found that different decisions will be affected by different factors. And when making decisions, the driver does not only consider the location relationship between the subject vehicle and the surrounding vehicles, but

also the location relationship among the surrounding vehicles. Besides, the average of factors under different decisions can explain why driving decisions are undertaken.

(2) According to the model calibration results, we can reveal the reason of different decisions, and prove the interpretability of the model. What's more, the result shows that the stimulus of space distance has great impact on the decision making.

The further work is to apply the model to the simulation platform to explore the impact of the micro driving behavior on the macroscopic traffic flow at the bottleneck.

REFERENCES

[1] Ahmed, K.I., 1999. Modeling Drivers' Acceleration and Lane Changing Behavior. Massachusetts Institute of Technology.

[2] Cao. K, et al. 2014. Maneuver Behavior identification and prediction for vehicles based on multi-hidden Markov model. Information and control 43(4),506-512

[3] Chandra S, Shukla S. Overtaking Behavior on Divided Highways Under Mixed Traffic Conditions[J]. Procedia - Social and Behavioral Sciences, 2012, 43(43):313-322.

[4] Daganzo, C.F., 2004. In traffic flow, cellular automata = kinematic waves. Transportation Research Part B 40 (5), 396–403.

[5] Gipps, P.G., 1981. A behavioural car-following model for computer simulation. Transportation Research Part B 15 (2), 105–111.

[6] Gipps, P.G., 1986. A model for the structure of lane-changing decisions. Transportation Research Part B 20 (5), 403–414.

[7] Gunay B. Car Following Theory with Lateral Discomfort[J]. Transportation Research Part B Methodological, 2007, 41(7):722–735.

[8] He Z C, Sun W B, Zhang L C, et al. Modeling and analysis of vehicle behavior at bottlenecks[J]. Acta Physica Sinica -Chinese Edition-, 2013, 62(16):168901-168901.

[9] Hou H. Research on Lane Change Intention Recognition Method for Freeway Driver [D]. Jilin University, 2013.

[10] Li K, Wang X, Xu Y, et al. Lane changing intention recognition based on speech recognition models [J]. Transportation Research Part C Emerging Technologies, 2016, 69:497-514.

[11] Peng J, Guo Y, Fu R, et al. Multi-parameter prediction of drivers' lane-changing behaviour with neural network model[J]. Applied Ergonomics, 2015, 50:207–217.

[12] Singh K, Li B. Estimation of Traffic Densities for Multilane Roadways Using a Markov Model Approach[J]. Industrial Electronics IEEE Transactions on, 2012, 59(11):4369-4376.

[13] Toledo, T., Katz, R., 2009. State-dependence in lane changing models. Transportation Research Record 2124, 81–88

[14] Worrall R D, Bullen A G, Gur Y. An Elementary Stochastic Model of Lane-Changing On a Multilane Highway[J]. Highway Research Record, 1970.

[15] Yang, Q., Koutsopoulos, H.N., 1996. A microscopic traffic simulator for evaluation of dynamic traffic management systems. Transportation Research Part C 4(3), 113–129.

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