MODELING OF CAR-FOLLOWING AND LANE-CHANGING BEHAVIOR ON THE EXPRESSWAY

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ABSTRACT

Due to the ability of capturing the complexity of traffic systems, traffic simulation has become one of the most used approaches for traffic planning, traffic design and traffic management. A wide variety of traffic simulation software is currently available on the market and is utilized by thousands of consultants, researchers and public agencies. With the popularity of traffic simulation, the car-following and lane-changing models, two of the most significant components in traffic simulation, have naturally attracted a lot of attention from traffic researchers. In this thesis, we also attempt to use some advanced computing technologies to model such driving behavior more realistically and accurately.

In order to achieve a complete insight in the state-of-the-art of traffic modeling, several typical car-following models are evaluated by using trajectory data from real traffic conditions and genetic-algorithm-based calibration method in the 3rd chapter. The models with calibrated parameters are validated not only under uncongested traffic conditions but also under congested traffic conditions. Unlike the results in previous study based on experimental data, there are obvious differences in the performance of these models.

In the 4th chapter, we investigate drivers' acceleration and deceleration behavior by using a mixed logit model. Compared to conventional car-following models, the vehicle type variable is used in the proposed model, which enables the model to allow for driving differences of different vehicle types. In addition, to intentionally avoid interference from lane-changing behavior, the model is estimated and validated by trajectory data in the high occupancy vehicle (HOV) lane. Estimation and validation

results sufficiently demonstrate reasonability, robustness, along with accuracy of the model. Finally, this model is applied to simulate 30-minute traffic conditions.

Reaction delay of the driver-vehicle unit varies greatly according to driver-vehicle characteristics and traffic conditions, and is an indispensable factor for modeling vehicle movements. In Chapter 5, by defining the time interval between the relative speed and acceleration, the gap and speed observed from real traffic as driver-vehicle reaction delay, a neural network for instantaneous reaction delay is built. Incorporating the reaction delay network into a neural-network-based car-following model, movements of nine vehicles which follow each other are simulated. Simulation results show that the models with instantaneous reaction delay apparently outperform the models with fixed reaction delay.

Lane changing has a significant impact on traffic flow characteristics and potentially reduces traffic safety. However, literature relating to lane changing is not comprehensive, largely owing to the inherent complexity of lane changing and a lack of large-scale data to analyze such behavior. In an effort to cope with these obstacles, in Chapter 6 we adopt a neural network (NN) model to capture the complexity of lane changing, and large-scale trajectory data are employed for model estimation and validation. For comparison purposes, a multinomial logit (MNL) model that was frequently accepted as a framework for lane changing in previous studies is also built. Comparison results show that NN model is more realistic than MNL model. Finally, the impact of heavy vehicles on driver's lane-changing decisions is quantitatively evaluated using the sensitivity analysis of the proposed NN model.

CHAPTER 1. INTRODUCTION

1.1 Motivation

Due to the ability of capturing the complexity of traffic systems, traffic simulation has become one of the most used approaches for traffic planning, traffic design and traffic management. A wide variety of traffic simulation software is currently available on the market and is utilized by thousands of consultants, researchers and public agencies (Barceló 2010; Bloomberg and Dale 2000; Hidas 2005; Yang and Koutsopoulos 1996). With the popularity of traffic simulation, the car-following and lane-changing models, two of the most significant components in traffic simulation, have naturally attracted a lot of attention from traffic researchers (Brackstone and McDonald 1999; Panwai and Dia 2005; Toledo 2007). A number of models have been proposed in the past decades to describe such driving behavior more realistically and accurately.

The concept of car following was first proposed by Reuschel (1950) and Pipes (1953), which assumed that the following vehicle controls its behavior with respect to the preceding vehicle in the same lane. Thereafter, considerable car-following models were developed to mimic this behavior more consistently with real traffic. In (Gipps 1981), equations of motion were accepted to describe driver's acceleration and deceleration behavior. According to stimulus and response relationship, Gazis et al. (1961) proposed a widely studied car-following model. Kikuchi and Chakroborty (1992) built a car-following model based on fuzzy logic theory. In addition, Nagel and Schreckenberg (1992) presented a typical cellular automata model to simulate vehicle movements. And, the model formulation in (Bham and Benekohal 2004) adopted the concept of cellular automata and car-following models. Besides, neural networks were also used to model car-following behavior (Panwai and Dia 2007).

According to previous studies, lane changing has a significant impact on traffic flow characteristics owing to the inference effect on surrounding vehicles (Daganzo et al. 1999). In addition, lane changing is also viewed as a key trigger in freeway breakdown (Duret et al. 2011; Jiang and Adeli 2004), and it potentially reduces freeway safety (Jin 2010; Mauch and Cassidy 2002). To describe such driving behavior more accurately, over the past two decades, several lane-changing models have been developed (Aghabayk et al. 2011; Gipps1986; Hidas 2002; Laval and Daganzo 2006). However, compared to the car-following model, literature relating to lane changing is less comprehensive. This may be owing to two reasons: the inherent complexity of lane changing and the absence of large-scale data to analyze such behavior. Unlike car following, lane changing is influenced not only by preceding and following vehicles in the same lane but also by leading and lagging vehicles in adjacent lanes (Moridpour et al. 2010). Besides, driver's decisions to change lane are also affected by driver characteristics (age, gender, driving experience) and driving attitudes (aggressive or conservative driver) (Sun and Elefteriadou 2012). As a result, the prediction of driver's lane-changing decisions is extremely complicated.

As the most important components in traffic simulation, a better understanding of driver car-following and lane changing behavior is, therefore, essential to enhance the accuracy of traffic simulation. Therefore, there is a need for improving the current understanding of drivers' car-following and lane-changing behavior at a microscopic level.

1.2 Problem Description

Researchers started paying attention to the car-following and lane-changing models as microscopic traffic simulation emerged as an important tool for studying traffic behavior and developing and evaluating different traffic control and management strategies. However, the existing car-following and lane changing models are rule-based and do not explicitly capture variability within driver and between drivers. Furthermore, the model parameters have not been estimated formally. More specifically, existing driving behavior models have the following important limitations.

1. Evaluation of some typical car-following models by using data from real traffic was seldom conducted.
2. The inherent approximate nature of human decision-making processes were not reflected in previous car-following and lane-changing models.
3. Instantaneous reaction delay of the driver-vehicle unit were not taken into consideration in previous studies where usually fixed reaction delay were adopted.
4. The factors that influence lane-changing decisions were not sufficiently included in previous lane-changing models.

5. Driving differences in the different types of vehicles were not accounted for in pervious driving models.

Given the inherent approximate nature of human decision-making processes and the understanding that car-following is such a decision-making process, deterministic car-following models are unable to capture the uncertainty of driving behavior. Although stochastic car-following models can somewhat reflect the imprecision of driving behavior, random mechanisms in the models do not directly relate to any driver or traffic characteristics. As common driving experiences, drivers perceive the current traffic conditions, use their knowledge to infer possible actions, and respond in an approximate manner. To reflect the inherent imprecision in the human perception and reasoning process, fuzzy inference models are adopted in (Kikuchi and Chakroborty 1992; Chakroborty and Kikuchi 1999). However, the difficulty in calibrating unobservable parameters greatly limits the applicability of these models (Toledo 2007; Chakroborty and Kikuchi 2003).

Reaction delay is a common characteristic of humans in operation and control, such as driving a car. The operational coefficients and delay characteristics of humans can vary rapidly because of changes in factors such as task demands, motivation, workload and fatigue. As mentioned above, research on car-following models historically has focused on exploration of different modeling frameworks and variables that affect this behavior. Recently, researchers have recognized that reaction delay of each driver is an indispensable factor for the identification of car-following models since it affects traffic dynamics not only in a microscopic way but also macroscopically (Ma and Andréasson 2006). However, due to that the estimation of variations in reaction delay is almost impossible in classic paradigms, in the abovementioned car-following models reaction delay was all assumed to be fixed. Besides, in previous studies the delay within the mechanical system of a vehicle was usually neglected. In fact, the time that a vehicle takes to respond to a request (decelerating, accelerating, steering) depends greatly on the vehicle and roadway conditions, and is different for different types of vehicles (motorcycle, car, heavy vehicle). For modeling vehicle movements more realistically, vehicle reaction delay should also be considered.

Besides, compared to the car-following model, literature relating to lane changing is less comprehensive. This may be owing to two reasons: the inherent complexity of lane changing and the absence of large-scale data to analyze such behavior. Unlike car following, lane changing is influenced not only by preceding and following vehicles in the same lane but also by leading and lagging vehicles in adjacent lanes (Moridpour et al. 2010). Besides, driver's decisions to change lane are also affected by driver characteristics (age, gender, driving experience) and driving attitudes (aggressive or conservative driver) (Sun and Elefteriadou 2012). As a result, the prediction of driver's lane-changing decisions is extremely complicated. On the other hand, models should be estimated and validated by field data (Hollander and Liu 2008). However, most of the previous lane-changing models were proposed without rigorous estimation and validation, largely owing to a lack of available data (Gipps1986; Hidas 2002).

1.3 Thesis Contributions

The objective of this research is to improve modeling of driving behavior. This thesis contributes to the state-of-the-art in driving behavior modeling in the following aspects:

- In order to achieve a complete insight in the state-of-the-art of traffic modeling, several typical car-following models are evaluated by using trajectory data from real traffic conditions and genetic-algorithm-based calibration method.
- We investigate drivers' acceleration and deceleration behavior by using a mixed logit model. Compared to conventional car-following models, the vehicle type variable is used in the proposed model, which enables the model to allow for driving differences of different vehicle types. In addition, to intentionally avoid interference from lane-changing behavior, the model is estimated and validated by trajectory data in the high occupancy vehicle (HOV) lane.
- The driver-vehicle reaction delay is defined by the time interval not only between the relative speed and acceleration but also between the gap and speed of the vehicle.
- A neural network for instantaneous reaction delay is trained by observed delay samples and then compared with a previous piecewise linear reaction delay model. Incorporating the reaction delay network into a neural-network-based car-following model, movements of nine vehicles which follow each other are simulated.

- A detailed analysis of left and right lane changes is conducted, which suggests that the left and right lane changes are asymmetric and incentivized by different motivations.
- A neural network model that can completely account for the impact of surrounding vehicles on lane-changing decisions is developed. In addition, the proposed NN model clearly outperforms a multinomial logit model, which was frequently adopted as a framework for lane changing in previous studies, both in model estimation and validation processes.
- The impact of heavy vehicles on driver's lane-changing decisions is quantitatively evaluated using the sensitivity analysis of the proposed NN model.

1.4 Thesis Outline

The thesis is composed of seven chapters. In Chapter 2, the data sets used in this thesis is introduced. Several typical car-following models are evaluated by using trajectory data from real traffic conditions and genetic-algorithm-based calibration method in Chapter 3. In the 4th chapter, we investigate drivers' acceleration and deceleration behavior by using a mixed logit model. In Chapter 5, by defining the time interval between the relative speed and acceleration, the gap and speed observed from real traffic as driver-vehicle reaction delay, a neural network for instantaneous reaction delay is built. Incorporating the reaction delay network into a neural-network-based car-following model, movements of nine vehicles which follow each other are simulated. In an effort to cope with the obstacles of modeling lane-changing behavior, in Chapter 6 we adopt a neural network model to capture the complexity of lane changing, and large-scale trajectory data are employed for model estimation and validation. Finally, conclusions and directions for future research are presented in Chapter 7.

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CHAPTER 2. DATA SETS

The data sets which are used in this study was prepared by Cambridge Systematics (2005a,b) incorporated for the Federal Highway Administration as a part of Next Generation SIMulation NGSIM project. In December 2005, NGSIM provided the video images of two sections of two highways in California: (1) Hollywood Freeway, (US-101) and (2) Berkeley Highway (I-80). Subsequently, a comprehensive vehicle trajectory data set was developed through processing the video images. Detailed information about observed vehicles, (vehicle type and size, lane ID, two-dimension position, speed and acceleration) was extracted from video data, together with information about the preceding and following vehicles.

2.1 US-101 Data Sets

Data presented in this section represent travel on the southbound direction of U.S. Highway 101 (Hollywood Freeway) in Los Angeles, California. This data was collected using eight video cameras mounted on a 36-story building, 101 Universal City Plaza, which is located adjacent to the U.S. Highway 101 and Lankershim Boulevard interchange in the Universal City neighborhood.

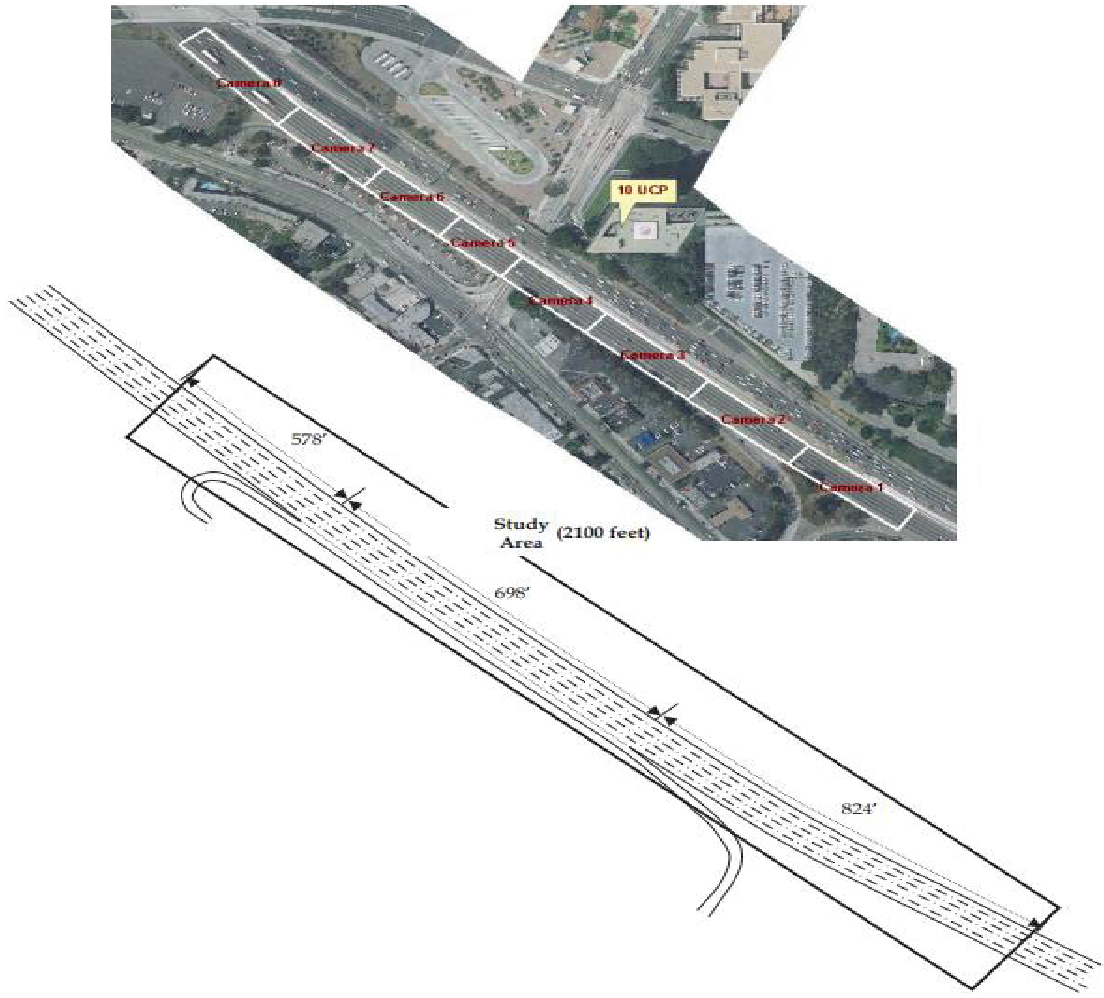

Fig. 2.1 U.S. 101 study area schematic and camera coverage

Table 2.1 Traffic composition and traffic flow characteristics in U.S. 101 data sets

Number of automobiles	Number of heavy vehicles	Number of motorcycles
5919 (97.0%)	137 (2.2%)	45 (0.7%)
Flow rate (veh/hr)	Average speed (km/hr)	Density (veh/km)
8077	35.0	231

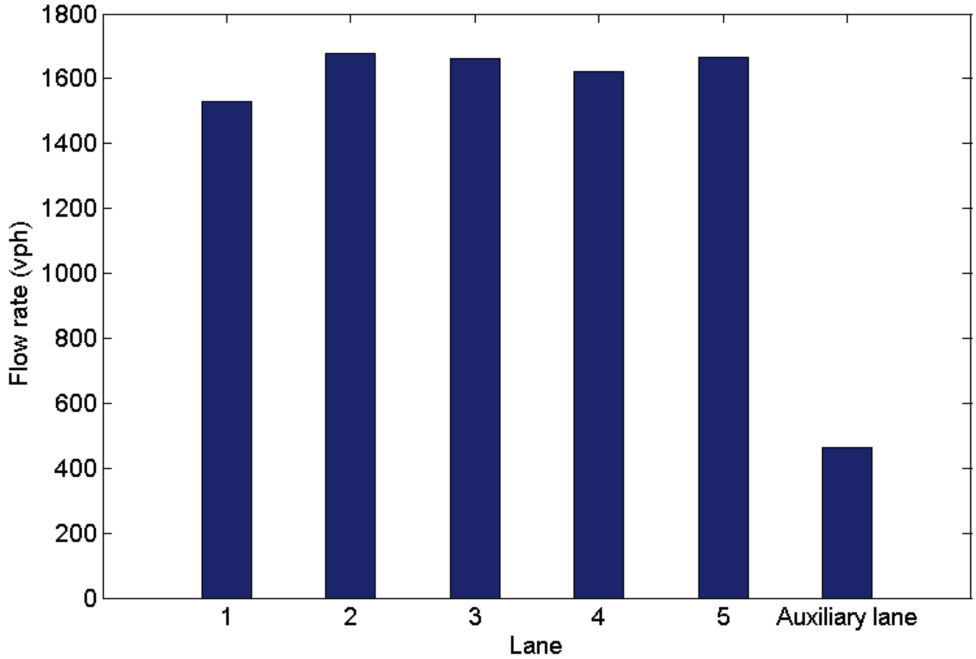

Fig. 2.2 Flow by each lane during 7:50 and 8:05 on U.S. 101 study site

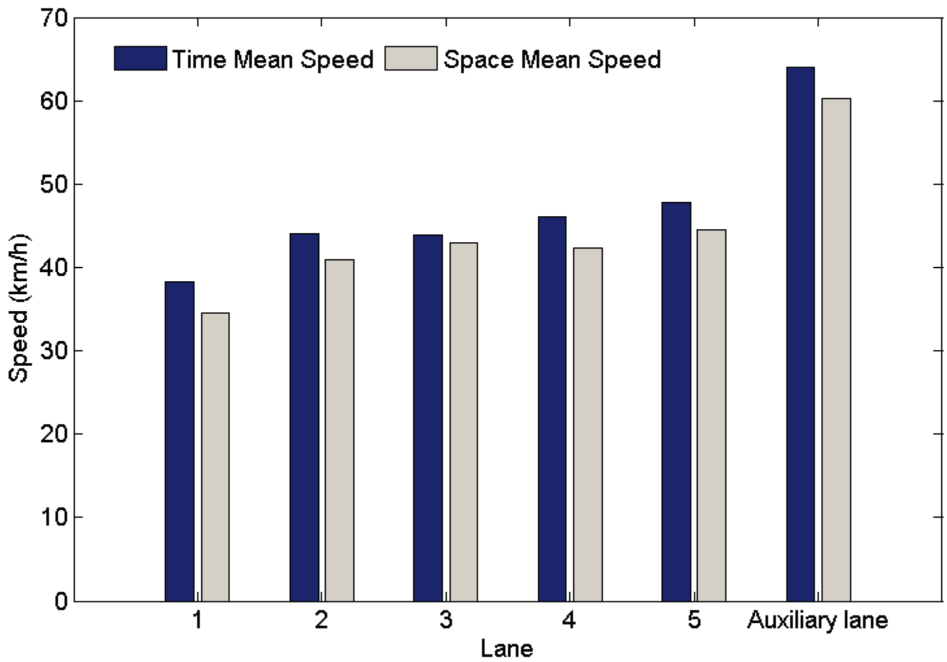

Fig. 2.3 Speed by each lane during 7:50 and 8:05 on U.S. 101 study site

Fig. 2.1 provides a schematic illustration of the location for the vehicle trajectory data sets. The site was approximately 640 m in length, with five mainline lanes throughout the section. An auxiliary lane is present through a portion of the corridor between the on-ramp at Ventura Boulevard and the off-ramp at Cahuenga Boulevard. Lane numbering is incremented from the left-most lane.

Video data were collected using eight video cameras, camera 1 through 8, with camera 1 recording the southernmost, and camera 8 recording the northernmost section of the study area, as shown in Fig. 2.1.

Data reflecting congested traffic conditions in morning peak periods were collected during 7:50 am and 8:35 am on June 15, 2005. Traffic composition and traffic flow characteristics are listed in Table 2.1. In addition, the data were collected in clear weather, good visibility, and dry pavement conditions.

Fig. 2.2 and Fig. 2.3 show the flow and speed by each lane during 7:50 and 8:05 on U.S. 101 study site. The time mean speed and space mean speed are defined as follows:

$$TMS(t,s) = \frac{\sum_i v(t,s)_i}{n(t,s)}, \qquad SMS(t,s) = \frac{\sum_i d(t,s)_i}{\sum_i tt(t,s)_i}, \tag{2.1}$$

where,

TMS(t,s) = Time Mean Speed in section s during time period t measured at midsection;

SMS(t,s) = Space Mean Speed in section s during time period t;

$v(t,s)_i$ = Instantaneous speed of vehicle i in section s during time period t measured at midsection;

$n(t,s)$ = Number of vehicles traversing section s during time period t;

$d(t,s)_i$ = Distance traveled by vehicle i in sections s during time period t;

$tt(t,s)_i$ = Travel time of vehicle i in section s during time period t.

2.2 I-80 Data Sets

Data presented in this section represent travel on the northbound direction of Interstate 80 in Emeryville, California. This data was collected using seven video cameras mounted on a 30-story building, Pacific Park Plaza, which is located in 6363 Christie Avenue and is adjacent to the interstate freeway I-80. The University of California at Berkeley maintains traffic surveillance capabilities at the building and the segment is known as the Berkeley Highway Laboratory (BHL) site.

Fig. 2.4 provides a schematic illustration of the location for the vehicle trajectory data sets. The site was approximately 503 m in length, with an on-ramp at Powell Street. The off-ramp at Ashby Avenue is just downstream of the study area. Lane numbering is incremented from the left-most lane (the high-occupancy vehicle (HOV) lane).

Video data were collected using seven video cameras, camera 1 through 8, with camera 1 recording the southernmost, and camera 7 recording the northernmost section of the study area, as shown in Fig. 2.4.

Data reflecting congested traffic conditions during afternoon peak periods were collected during 4:00 pm and 4:15 pm, 5:00 pm and 5:30 pm on April 13, 2005. Traffic composition and traffic flow characteristics are listed in Table 2.2. Fig. 2.5 and Fig. 2.6

show the flow and speed by each lane during 5:15 and 5:30 on I-80 study site. In addition, the data were collected in clear weather, good visibility, and dry pavement conditions.

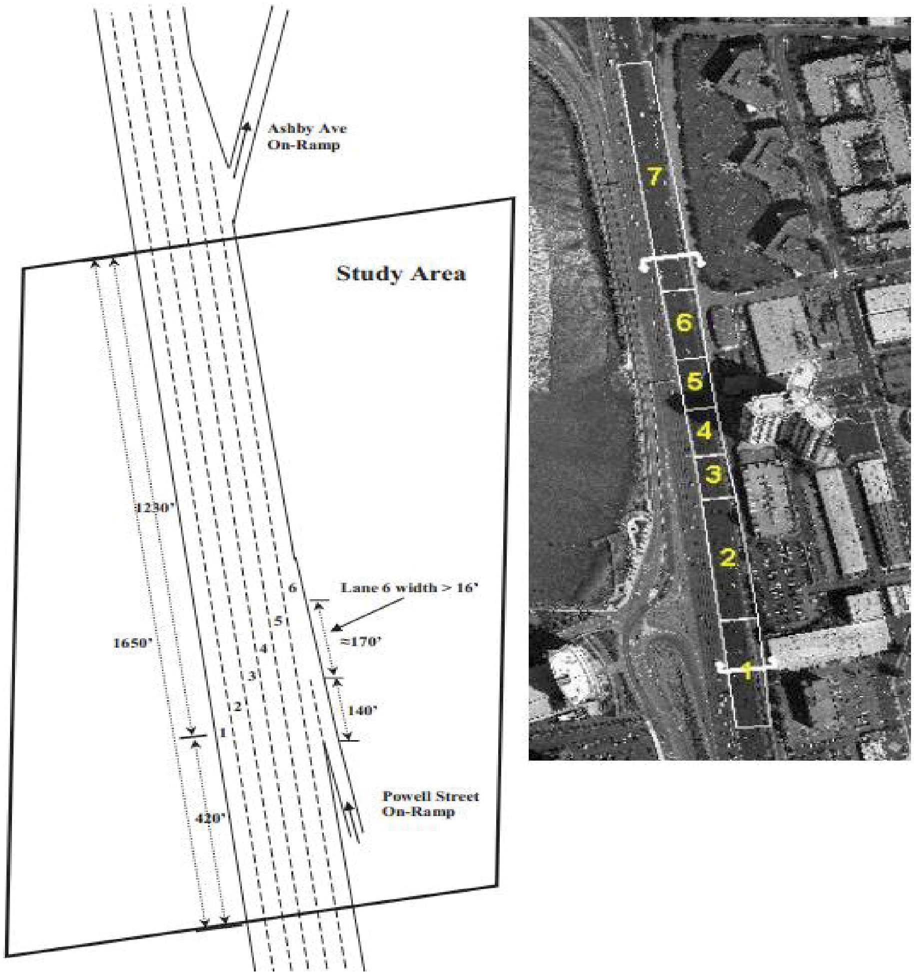

Fig. 2.4 I-80 study area schematic and camera coverage

Table 2.2 Traffic composition and traffic flow characteristics in I-80 data sets

Number of automobiles	Number of heavy vehicles	Number of motorcycles
3466 (95.6%)	119 (3.3%)	41 (1.1%)
Flow rate (veh/hr)	Average speed (km/hr)	Density (veh/km)
7252	27.9	300

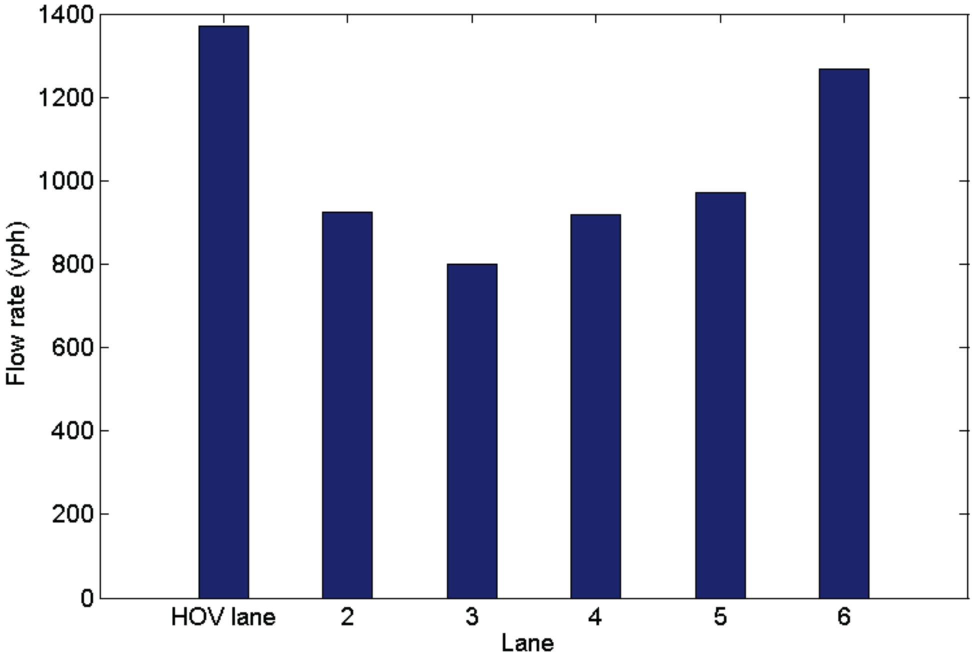

Fig. 2.5 Flow by each lane during 5:15 and 5:30 on I-80 study site

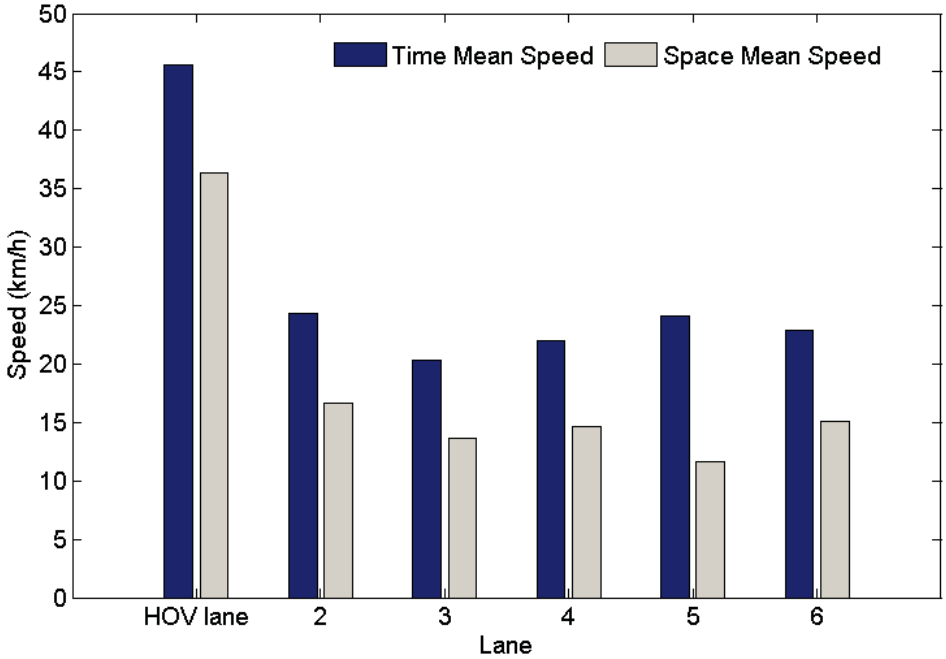

Fig. 2.6 Speed by each lane during 5:15 and 5:30 on I-80 study site

Besides, in order to alleviate the noise in the data (Punzo et al. 2011), the moving-average filter for a duration of one second is applied to all vehicle trajectories before data analysis in this thesis.

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CHAPTER 3. EVALUATION OF CAR-FOLLOWING MODELS USING TRAJECTORY DATA FROM REAL TRAFFIC

3.1 Introduction

Traffic simulation, as an effective tool for traffic system analysis and traffic management, has become very popular in recent years. Car-following model and lane-changing model, the most significant components in traffic simulator, attract considerable attention from traffic researchers. A number of car-following and lane-changing models have been proposed to describe real traffic more accurately.

In order to find out the most suitable model to be applied in traffic simulation, researchers compared some of the these models by using field data, experimental data, or even assumed data at the microscopic or macroscopic level, especially for car following models (Olstam and Tapani 2004; Panwai and Dia 2005; Rakha and Crowther 2002, 2003; Ranjitkar et al. 2005a).

As pointed out in their conclusions (Olstam and Tapani 2004; Ranjitkar et al. 2005a), a comprehensive comparison with complex real traffic data is a compelling need to achieve a complete insight in the state-of-the-art of traffic modelling. Under such requirement, several typical car-following models are evaluated by using trajectory data from real traffic condition and genetic-algorithm-based calibration method in this study.

The evaluated models are stimulus-response model (Gazis et al. 1961), safety distance model (Gipps 1981), Newell model (Newell 2002), cellular automata model (Nagel and Schreckenberg 1992), optimal velocity model (Bando et al. 1995). Although these models were compared in previous studies (Brockfeld et al. 2004; Ranjitkar et al. 2005a) based on experimental data, unlike their conclusions, the differences in the performance of these models are obvious in this study.

This chapter is composed of five sections. The subsequent section briefly introduces the car-following models to be evaluated, followed by the third section which includes the introduction of objective function, genetic algorithm, and data sets to be used in current study. The evaluation results are put into the fourth section. The last section is devoted to the conclusion of this study.

3.2 Car-following Models

The concept of car-following was perhaps first proposed by Reuschel (1950) and Pipes (1953), which assumed that the following vehicle controls its behaviour with respect to the preceding vehicle in the same lane. As one of the most important components in traffic simulator, in the past decades considerable car-following models were developed to mimic this process more consistently with real traffic (see (Brackstone and McDonald 1999) and references therein). In this study, the following models are discussed.

3.2.1 Stimulus-response model (SRM)

The stimulus-response kind models are probably the earliest and most studied car-following models, which express the suggestion that a driver of a vehicle responses to a given stimulus according to a relationship: *Response* = λ * *Stimulus*.

The typical one in stimulus-response family is perhaps the one proposed by Gazis et al. (1961):

$$a_n(t+T) = \alpha v_n^{\beta}(t+T)\frac{\Delta v_n(t)}{\Delta x_n^{\gamma}(t)} \tag{3.1}$$

where $a_n(t)$, $v_n(t)$, $x_n(t)$ and T are the acceleration, velocity, position and reaction time of the subject vehicle, respectively. Moreover, $\Delta v_n(t)$ and $\Delta x_n(t)$ are the relative velocity and relative spacing between the subject vehicle and its leader, vehicle n and vehicle n-1, at time t. Besides, α, β, γ are parameters needed to be calibrated. Brackstone and McDonald (1999) summarized the works conducted by previous researchers in calibrating this kind model, alone with problems appearing in their study in detail.

3.2.2 Safety-distance model (SDM)

Taking safety reaction time into account, Gipps (1981) developed a model consisting of two components, acceleration and deceleration, using variables directly corresponding to obvious characteristics of drivers and vehicles. Assumed that if one vehicle is not affected by its leader, the acceleration should increase with velocity then decrease to zero as the vehicle approaches the desired velocity. The desired velocity limitation fitted from field data is presented as:

$$v_n^a(t+T) \le v_n(t) + 2.5Ta_n(1-\frac{v_n(t)}{V_n})\sqrt{0.025+\frac{v_n(t)}{V_n}} \tag{3.2}$$

where $a_n(t)$ is the maximum acceleration that the driver in vehicle n wishes to apply and V_n is desired velocity.

The velocity limitation that can avoid collision when the leading vehicle brakes to slow down was derived from the equation of motion, written as:

$$v_n^d(t+T) \le b_nT + \sqrt{b_n^2T^2 - b_n[2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t)T - \frac{v_{n-1}^2(t)}{\hat{b}}]} \tag{3.3}$$

where b_n is the most severe braking that the driver of vehicle n wishes to undertake ($b_n < 0$), s_{n-1} is the effective size of vehicle n-1 and $\hat{b}$ is the estimation of b_{n-1}.

Combining the limitation (2) and (3), the velocity of vehicle n at time t+T is set as:

$$v_n(t+T) = \min\{v_n^a(t+T), v_n^d(t+T)\} \tag{3.4}$$

which can ensure drivers to achieve desired velocity as far as possible, and to avoid the collision with the preceding vehicle, meanwhile. The car-following model implemented in microscopic traffic simulator AIMSUN is based on this model.

3.2.3 Newell model (NM)

With different logic, Newell (2002) proposed a new approach to model car-following behaviour based on the analysis of time-space trajectory, assuming that the time-space trajectory for vehicle n-1 and n is essentially the same except for a translation in time and space. Under the supposition that there is a linear relationship between the spacing s_n and the velocity v, the logic behind Newell's simple car-following model can be demonstrated by Fig. 3.1. From the time displacement τ_n and space displacement d_n in Fig. 3.1, one can get the following relationship:

$$d_n + v\tau_n = s_n, d_n + v'\tau_n = s'_n. \tag{3.5}$$

It is important to note that τ_n is not the reaction time, which is the time needed for driver n to reach preferred spacing at a new velocity. Therefore, the simple car-following model proposed by Newell can be written as:

$$x_n(t+\tau_n) = x_{n-1}(t) - d_n. \tag{3.6}$$

In previous study, this model was considered to be able to perform as well as complex models (Brockfeld et al. 2004; Ranjitkar et al. 2005a). Furthermore, Ahn (2004) verified this model by measuring vehicles discharging form long queues at signalized intersections.

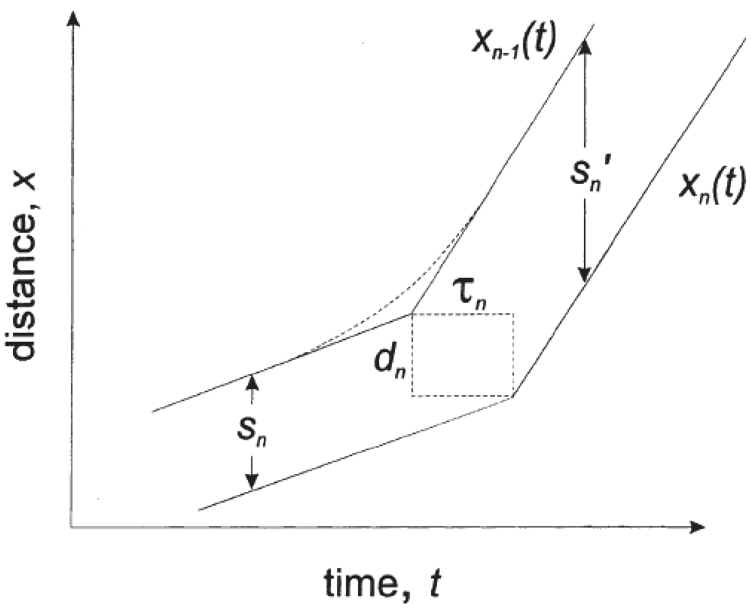

Fig. 3.1 Linear approximation to vehicle trajectories.

3.2.4 Optimal velocity model (OVM)

Under the assumption that the acceleration is determined by the difference between the actual velocity and optimal velocity, Bando et al. (1995) proposed a charming car-following model. The dynamical equation is presented as:

$$\frac{dv_n(t)}{dt} = \frac{1}{T}[V(\Delta x_n(t)) - v_n(t)] \tag{3.7}$$

where

$$V(\Delta x_n(t)) = \tanh(\Delta x_n(t) - 2) + \tanh(2) \tag{3.8}$$

is called the optimal velocity function.

Bando's model can describe many properties of real traffic, such as the instability of traffic flow, the evolution of traffic congestion and formation of stop-and-go phenomenon. In addition, it was highly praised by physicists due to its feasibility in theory analysis. Although it is successful in physical community, a few studies were conducted to evaluate the model with real traffic data.

3.2.5 Cellular automata model (CAM)

CA models are based on a coarse description of driving behaviour by a discrete representation of both time and space. Road length is divided into cells of equal size (typically 7.5 meters long). Each cell has two states, occupied or not, depending on the presence of a vehicle. Each time step one vehicle's velocity and position are updated according to its desired velocity and whether there is a vehicle blocking its movement in front. Nagel and Schreckenberg (1992) introduced stochastic perturbations into updating rules and presented a typical CA model:

$$\tilde{v}_n(t+1) = \min(v_n(t)+1, g_n(t), V_{\max})$$
$$v_n(t+1) = \begin{cases} \max(\tilde{v}_n(t+1)-1, 0), C_{rand} \leq P \\ \tilde{v}_n(t+1), \qquad otherwise \end{cases} \tag{3.9}$$
$$x_n(t+1) = x_n(t) + v_n(t+1)$$

where $\tilde{v}_n(t+1)$ is an temporary value and $g_n(t) = x_{n-1}(t) - x_n(t) - 1$. C_{rand} is a random number ranging from [0, 1] and P is a given velocity reduction probability.

Due to computational efficiency and simple rules, CA model can be used for large-scale traffic simulation. TRANSIM simulator developed by Los Alamos National Lab is the one based on CA model. Some researchers also took other rules into account, according to real traffic phenomena, such as slow-to-start rule in which vehicles are slower to accelerate from standstill, anticipation-based rule that predicts the movement of the leading vehicle in advance. For a detailed review, readers are referred to (Schadschneider 2006).

3.3 Parameter Calibration

As is well known, model's performance depends not only on the inherent structure of model but also on parameters included in the model. Consequently, on the one hand, researchers work on the improvement of the structure of the models, and on the other hand, they seek to find out appropriate optimization techniques to achieve optimal values for parameters. Hollander and Liu (2008) summarized the methodologies used in calibration process, and provided the general principles for traffic analysts.

3.3.1 Objective function

As shown in (Hollander and Liu 2008), various objective functions can be used in optimization techniques. In this study, the one proposed by Kesting and Treiber (2008) is used:

$$F_{rel}[s^{sim}] = \sqrt{\frac{1}{\Delta T}\sum_{i=1}^{\Delta T}\left(\frac{s_i^{sim} - s_i^{data}}{s_i^{data}}\right)^2} \tag{3.10}$$

where s^{data} and s^{sim} are the real and simulated data respectively, and ΔT is the total time interval. As pointed out by Kesting and Treiber (2008), F_{rel} is sensitive for small deviation in spacing, and spacing is suitable for the error measurement due to that when optimized in terms of spacing the average velocity errors will also be automatically reduced.

Furthermore, additional constraints are imposed to the objective function in order to avoid collision and negative velocity value in the simulation process, presented as:

$$x_{n-1}(t) \geq x_n(t) + S_{\min}, v_n(t) \geq 0, \forall t \in [1, \Delta T] \tag{3.11}$$

where S_{min} is the minimum spacing between two successive vehicles at rest.

3.3.2 Genetic algorithm (GA)

Typically, the motivation of using GA in optimization problems is due to the globality, parallelism and robustness of GA. In addition, GA is simple and powerful in its search improvement, and not fundamentally limited by restrictive assumption about the search space. In fact, GA was successfully used in many aspects of traffic field, such as optimal traffic signal control (Ceylan and Bell 2004; Memon and Bullen 1996), urban transit system design (Agrawal and Mathew 2004; Pattnaik et al. 1998), traffic assignment (Reddy and Chakroborty 1999; Sadek et al. 2007; Zhou et al. 2006), and traffic model calibration (Cheu et al. 1998; Kesting and Treiber 2008; Ranjitjar et al. 2005b).

3.3.3 Data sets

The data used in this study were collected by the NGSIM program from 4:00 pm to 5:30 pm on a segment of Interstate freeway I-80 in Emeryville (San Francisco), California. Two successive vehicles with mean velocity 2.18 m/s and 2.23 m/s denoted by C1 and C2 are selected for parameter calibration. Moreover, another two pair vehicles with mean velocity 1.52 m/s and 1.54 m/s, 5.38 m/s and 6.27 m/s, denoted by V1, V2 and V3, V4 , are chosen for model validation.

Fig. 3.2 exhibits position and velocity changes of all tested vehicles. It is clear that data used in calibration process are under congested traffic condition represented by the stop-and-go phenomenon. Data used in the first validation process, V1 and V2, are similar to calibration data but under more severe congested condition. V3 and V4 representing the non-congested traffic condition are used for the second validation. It is worth pointing out that three pair vehicles are from different lanes and different time intervals, so they are independent to each other and suitable for calibrating and validating models, respectively.

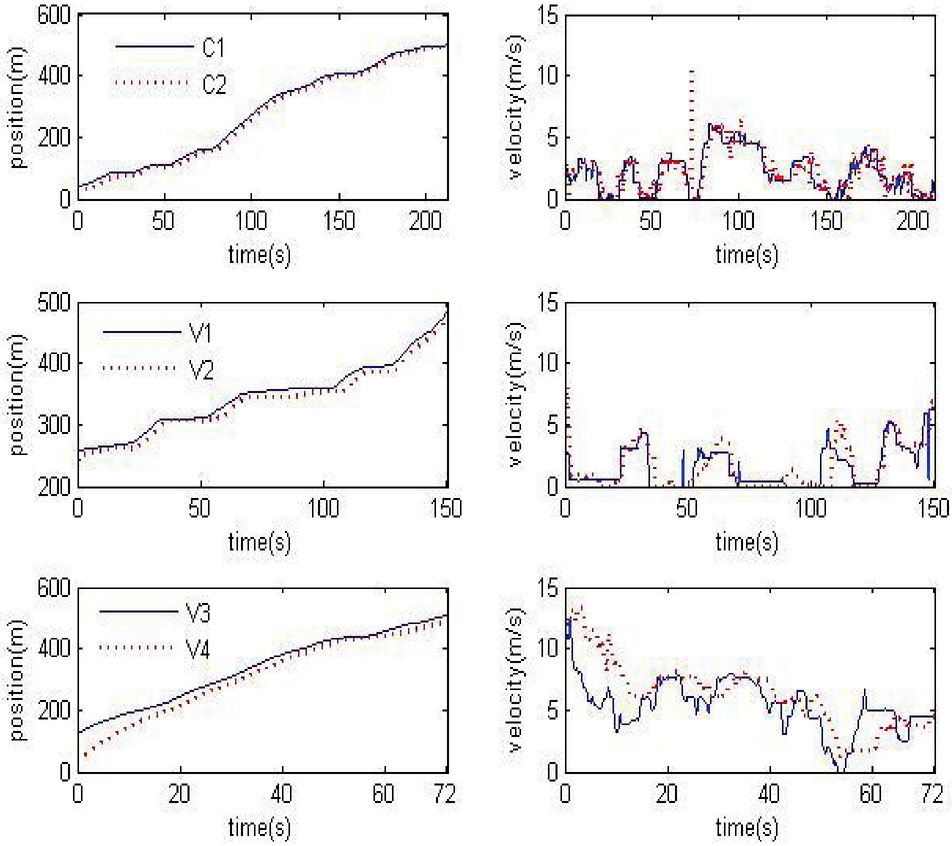

Fig. 3.2 Position trajectories and velocity profiles of tested vehicles.

3.4 Model Evaluation

In simulation run, the time step is set to be 0.1 seconds in order to keep pace with video data, and all the models are modified to adopt such time step. Moreover, all the preceding vehicles are updated according to the real value and all the following vehicles are updated according to rules of the discussed models. Additionally, parameters in Genetic

Algorithm are always the same for all of the models in order to evaluate them by the same criterion. The calibration and validation of these models are implemented in Matlab.

For SRM and OVM, due to nonlinear differential structure and no existence of analytical solutions, first order difference algorithm is implemented to calculate their numerical solutions. In addition, the constant 2 in optimal velocity Eq. 3.8 is treated as parameter denoted by C. For CAM, the length of one cell is taken as one meter and velocity is the corresponding integer value in order to improve the accuracy of this model. Moreover, the proceeding value per time step in acceleration and random reduction rule is seen as parameter denoted by D_{min}, different from that in (Nagel and Schreckenberg 1992) defined as one site per time step.

3.4.1 Calibration results

The calibration results are exhibited in Table 3.1. From it, one can see that the error rates for most models are between 17.6% and 31.29%, which is consistent with previous study (Brockfeld et al. 2004; Ranjitkar et al. 2005a), apart from OVM. This result also indicates that GA is suitable for being used in calibrating car-following models, which can achieve optimal parameter value for most models. It is also clear that SDM with the most parameters has the lowest error rate among these models. The reaction time T is smaller and the estimation to deceleration of the preceding vehicle $\hat{b}$ is larger than that usually assumed. Probably, this may be caused by the collision-avoidance limitation v_n^d in the model under the congested traffic condition.

Table 3.1 Calibration results of models under investigation.

Model	Parameter	Range	Calibrated result	Error rate
SRM	T	0~1	0.4	18.48%
	α	-4~4	1.38	
	β	-4~4	-0.27	
	γ	-4~4	-0.07	
SDM	T	0~1	0.1	17.6%
	a_n	2~6	2	
	V_n	5~50	40	
	b_n	-10~-4	-4	
	s_{n-1}	5~20	6.56	
	$\hat{b}$	-10~-4	-10	
NM	τ_n	0~100	0.1	31.29%
	d_n	0~20	8.84	
OVM	T	0.01~20	0.05	750%
	C	0~100	6.36	
CAM	D_{min}	1~10	6	24.27%
	V_{max}	10~40	26	
	P	0~1	0.7	

Moreover, the result also shows that SRM has acceptable error rate, although the parameters calibrated in this study are not similar to that calibrated by previous researchers (Brackstone and McDonald 1999), and a relatively longer reaction time is observed. Due to the simple rules, NM and CAM have rather higher error rate, but surprisingly, even with discrete variables the error rate in CAM is lower than that in NM. In addition, it is disappointed to see that OVM has incredible error rate although this model is popular in the physical community.

Fig. 3.3 presents a visual comparison between real and simulated value of the velocity for vehicle C2. SRM, SDM and NM can depict the real velocity change accurately, which are consistent with the spacing error rate in Table 3.1. Because of discrete value in velocity, the velocity error rate in CAM seems larger than spacing error rate in Table 3.1. After some simulation step, one can see that the velocity in OVM retains a constant value which is caused by the property of tanh(x) function. When spacing $\Delta x_n(t)$ exceeds a certain big value, tanh(x) function is not sensitive to small change and prone to maintain a constant value, which is also the reason for the incredible spacing error rate in Table 3.1.

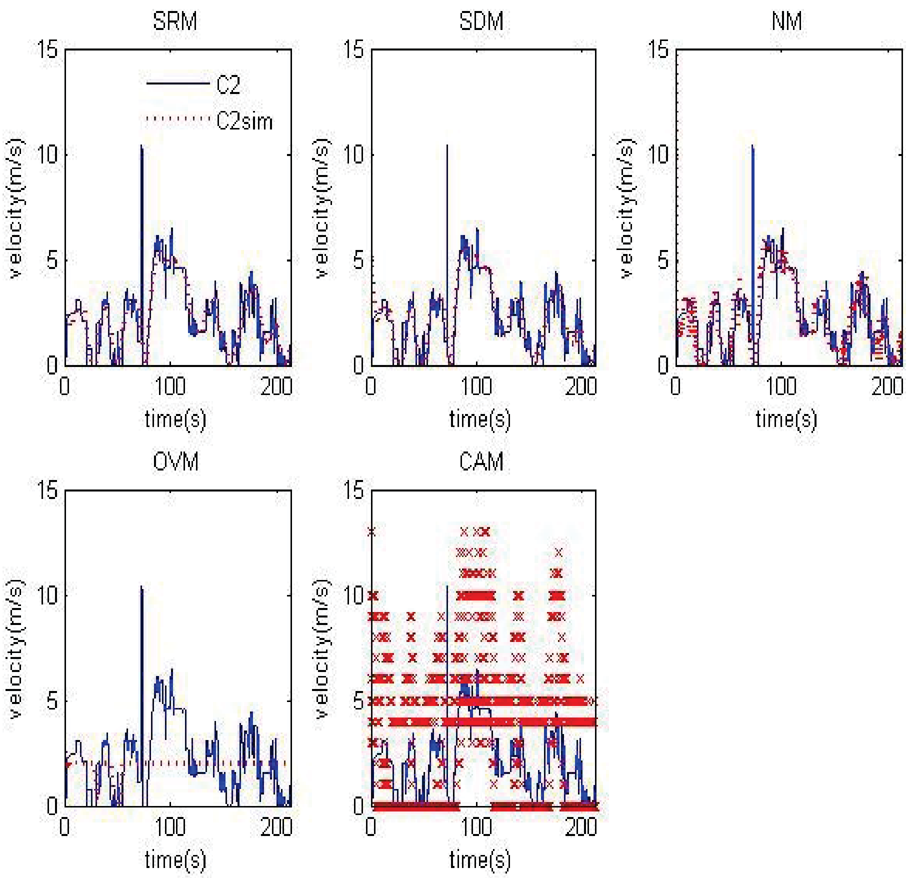

Fig. 3.3 Comparison of velocity between real and simulated value for vehicle C2.

3.4.2 Validation results

In what follows using the calibrated parameters in Table 3.1, the robustness of all models investigated in this paper is validated. In fact, this is a very significant part in evaluating models, although it is rarely conducted by previous researchers. Even with the excellent performance in calibration process it cannot be guaranteed that models never generate serious errors, such as collision or negative velocity value, in application stage, which is known as over-fitting problem. Typically, for one model, over-fitting problem is defined as the infeasibility of generalizing to other situation due to the adaptation to a particular situation.

Table 3.2 shows the spacing error rate calculated by using Eq. 10 in twice validation processes. It clearly can be seen in the first validation process, SRM and OVM generate collision or negative velocity value error, while the remainders achieve acceptable error rates, although a little higher than those in calibration process. Fig. 3.4 presents the comparison of the position and velocity between real and simulated data in the first validation process. From it, one can see that there are nearly no differences in position between real and simulated data, and the deviations in velocity between real and simulated data are also tiny except for CAM.

In the second validation process, due to the rather big differences between calibration and validation data most models yield serious error, only SRM and CAM can survive with higher error rate. Fig. 3.5 provides a visual comparison in position and velocity between real and simulated data. The position and velocity differences between real and simulated data are more apparent in relation to the first validation process.

From the validation results, CAM is the only one that can survive in both validation processes due to the collision-avoidance and negative-velocity-avoidance mechanism in its rules. Furthermore, even with discrete variables, CAM is able to maintain an acceptable error rate, while other models either make serious error or produce rather higher error rate. It also can be seen that SRM and SDM have the over-fitting problem, that is, they perform better than other models in calibration process or validation process with high similarity to calibration process, whereas under the situation

Table 3.2 The spacing error rate of tested models in validation process.

Model	SRM	SDM	NM	OVM	CAM
Validation 1	error	24.68%	34.75%	error	31.69%
Validation 2	345.80%	error	error	error	49.20%

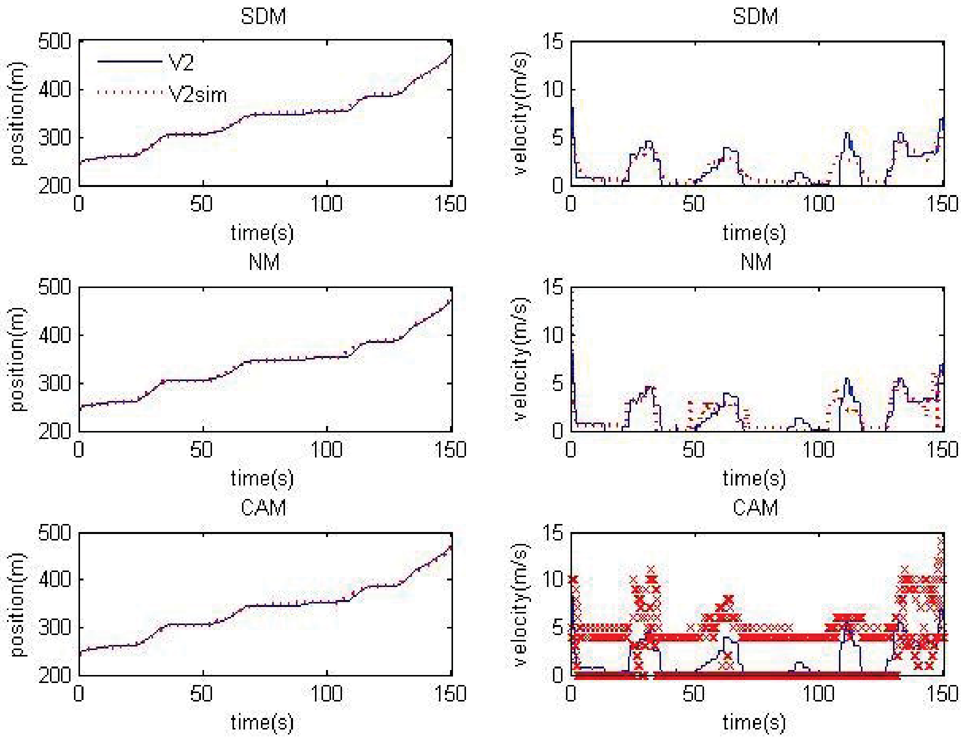

Fig. 3.4 Comparison of position and velocity between real and simulated data in the first validation process

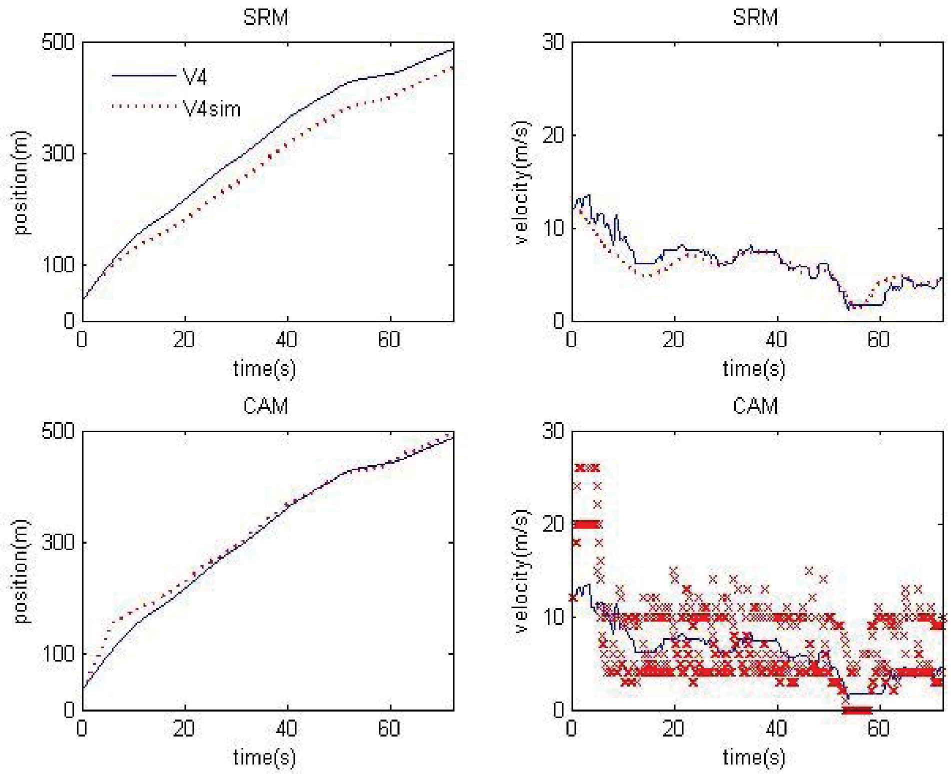

Fig. 3.5 Comparison of position and velocity between real and simulated data in the second validation process

with big differences to calibration process they generate rather higher error rate. This is due to that the number of parameters used in SRM and SDM are more than that used in other models, 4 and 6 respectively. Hence, the performance of SRM and SDM mostly depends on calibrated parameters not on the inherent structure of the models. So models with rather more parameters are prone to achieve better performance under particular situation but under other situation the over-fitting problem is likely to appear. The validation results also show that OVM is not suitable for real traffic simulation, because of the property of tanh(x) function. With rather simple rule and fewer parameters, NM generates larger error rate than other models except for OVM, which means it cannot describe traffic phenomenon accurately at microscopic lever. Besides, models with complex structure, such as SRM and OVM, cost more time than those with simple structure, such as NM and CAM, in simulation runs, which means they are not suitable for real time traffic simulation.

3.5 Conclusions

Several typical car-following models are evaluated by using field trajectory data and genetic-algorithm-based calibration method. The models with calibrated parameters are validated by using not only the uncongested traffic data but also congested traffic data. Unlike the results extracted from experimental data in (Brockfeld et al 2004; Ranjitkar et al 2005a), there are obvious differences in performances of the evaluated models. Models with complex structure, such as SRM and OVM, cost more time than those with simple structure, such as NM and CAM, in simulation process, which means they are not suitable for real time traffic simulation. Besides, SRM and OVM do not perform as well as expected in terms of calibration and validation results. Furthermore, models with more parameters such as SDM are easy to incur over-fitting problem in validation process, although they can mimic real traffic accurately in calibration process. Even with the very simple structure, NM and CAM reproduce the real traffic well both in calibration and validation process, especially the discrete CAM, the only one that can survive in both validation processes.

It is also observed that although most models under study simulate real traffic with high fidelity in calibration process, in validation process none of them is able to perform as well as in calibration process. From this point of view, using different parameters or even different models under different traffic condition seems to be feasible for simulating real traffic more accurately. In fact, this view can be confirmed by only adjusting the parameter V_{max} in CAM to 14 in the second validation process. Accordingly, the error rate can be reduced from 49.20% to 38.79%.

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CHAPTER 4. MODELING ACCELERATION AND DECELERATION BEHAVIOR IN HOV LANE BY USING DISCRETE CHOICE THEORY

4.1 Introduction

Traffic simulation, as an effective tool for traffic system analysis and traffic management, has become very popular in recent years. Various traffic simulators have been developed, and there are still some under construction. Car-following models and lane-changing models, the most significant components in traffic simulators, attract a lot of attention from traffic researchers. A number of models have been proposed in the past decades to describe such driving behavior more realistically and accurately (Bham and Benekohal 2004; Gazis et al. 1961; Gipps 1981; Gipps 1986; Gunay 2007; Hidas 2002; Kometani and Sasaki 1961; Nagel and Schreckenberg 1992; Newell 2002) . Meanwhile, there are also some researchers comprehensively analyzing such behavior by field observation or traffic experiment (Banks 2006; Ozaki 1991; Xing et al. 1991).

In this study, we pay attention to car-following models. The concept of car-following was first proposed by Reuschel (1950) and Pipes (1953), which assumed that the following vehicle controls its behavior with respect to the preceding vehicle in the same lane. Thereafter, considerable car-following models were developed to mimic this process more consistently with real traffic (see (Brackstone and McDonald 1999; Oguchi

2000) and references therein).

Typically, car-following models can be classified as continuous or discrete models. Gazis (1961) and Gipps (1986) used the second order differential equation and equations of motion to describe acceleration and deceleration behavior respectively, which are prominent examples of continuous car-following models. The prominent examples for discrete car-following models may be that proposed by Nagel and Schreckenberg (1992), Kikuchi and Chakroborty (1992), using cellular automaton model and fuzzy set theory.

In this study, we also assume drivers acceleration and deceleration behavior are discrete. Under this assumption, we attempt to apply discrete choice theory to model such driving behavior.

Discrete choice theory has been widely used in many fields of economics and traffic science (Asakura et al. 2001; Ben-Akiva and Lerman 1985; Bhat and Gossen 2004; Dia 2002; Revelt and Train 1998; Train 2003). Recently, Antonini et al. (2006) and Robin et al. (2009) used cross nested logit model to investigate pedestrian movements. Motivated by their study, a mixed logit model with alternative-specific parameters is adopted to investigate drivers acceleration and deceleration behavior, in this study. Unlike previous car-following models, the vehicle type variable is used, which makes the proposed model be able to allow for driving differences of different vehicle types. Variables minus reference values adopted in this study improve explicability of the proposed model. Additionally, to intentionally avoid interference from lane-changing behavior, this model is estimated and validated by trajectory data in the high occupancy vehicle (HOV) lane. Finally, due to the fact that the purpose of developing traffic models is to predict unknown traffic conditions, the model is applied to simulate 30-minute traffic conditions. Estimation, validation and simulation results sufficiently exhibit merits, together with defects of this model.

The paper is composed of seven sections. Model specification is in the subsequent section, followed by the introduction of data sets to be used in this study. Estimation, validation and simulation results are separately put into the fourth, fifth and sixth section. The last section is devoted to the conclusion and further discussion.

4.2 Model Specification

It is important to mention that, according to (McFadden and Train, 2000), the mixed multinomial logit model can approximate any random utility model, and the model proposed in this study is the result of an intensive modeling process, where many different specifications have been considered. Although an ordered logit or probit model can account for the ordinal nature of the deceleration/acceleration alternatives, it is unable to capture the correlation between deceleration/acceleration alternatives in the same group, as well as heterogeneity across choice occasions. Eluru et al. (2008) stated that the ordered logit or probit model has a limitation in that the threshold values are fixed across observations, which could lead to inconsistent model estimation. Although the model in (Eluru et al., 2008) addresses this limitation, the correlation between alternatives is overlooked. The nested logit model could deal with the correlation between alternatives, but heterogeneity across choice occasions is not taken into consideration. Besides, Brownstone and Train (1998) proved that a particular mixed logit model could be equivalent to a nested logit model. In addition to specifying the compound error term, the mixed logit model also allows for other random terms such as random alternative-specific constants. Hence, the mixed logit model is more flexible.

4.2.1 Alternatives

Based on current traffic conditions, it is assumed that drivers can make a judge about the acceleration or deceleration to be carried out in the next time step. As shown in Fig. 4.1, for convenience, acceleration and deceleration are discretized into five alternatives. Ma and Md stand for maximum acceleration and minimum deceleration, and we suppose that vehicles in this study have the same maximum acceleration and minimum deceleration. If alternative 4 or 5 is selected, drivers will accelerate at the rate of 0.4 or 0.8 times Ma, in next time step. Similarly, alternative 1 or 2 means decelerating at 0.8 or 0.4 times Md. And, if drivers intend to maintain current speeds, alternative 3 will be selected. Here, we clarify that due to few studies in acceleration and deceleration classification, the classification approach we used is to keep balance in acceleration and deceleration

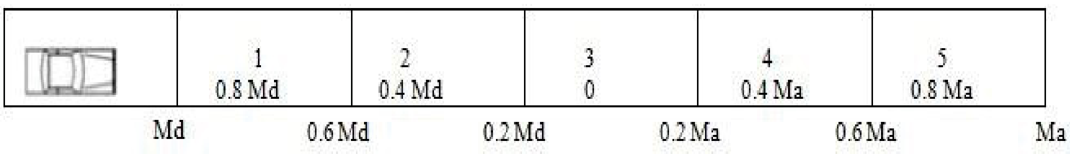

Fig. 4.1 Acceleration and deceleration alternatives for one driver.

intervals and observations, according to acceleration and deceleration distribution in the data sets to be used. Undoubtedly, other classification methods can also be considered.

In addition, it is important to note that, in order to avoid collision with its leader, some alternatives are unavailable under certain traffic conditions. For example, if alternative 5 is selected, there will be a collision with the preceding vehicle. Hence, it is necessary to identify the availability of each alternative in the next time step. In this study, we define the availability of each alternative as follows,

$$Av_{i\mathrm{n(t+1)}} = \begin{cases} 1, & \text{if} \quad Gap_{\mathrm{nt}} + v_{L\mathrm{nt}} - (v_{\mathrm{nt}} + AD_i) > C_{gap}, \\ 0, & \text{otherwise} \quad i \in [1,2,3,4,5] \end{cases} \tag{4.1}$$

It is assumed that when the preceding vehicle maintains the current speed v_{Lnt} and the subject vehicle n selecting alternative i accelerates or decelerates at the rate of AD_i, the gap between them should be greater than the critical gap C_{gap} in the next time step. C_{gap} is taken as the mean gap of stationary vehicles in the data set to be used. Gap_{nt} and v_{nt} are the current gap and speed for the vehicle n.

According to the availability, alternatives faced by drivers vary with traffic conditions. Defining the availability of alternatives can improve the accuracy of the proposed model by setting the choice probability of unavailable alternatives as zero.

4.2.2 Mixed logit model

As is well known that mixed logit model is a highly flexible model that can approximate any random utility model (McFadden and Train 2000), we adopt the mixed logit model with random constants to investigate acceleration and deceleration behavior in this study.

Like the standard logit model, the utility function is defined as,

$$U_{int} = V_{int} + \varepsilon_{int}, i \in [1,2,3,4,5], n \in [1, N], \tag{4.2}$$

where V_{int} is the observed utility and ε_{int} is the unobserved error term at time t. Besides, i stands for the alternative defined in Fig. 4.1 and N is the number of drivers in the data set to be used.

According to driving experiences, current traffic conditions (such as, speed, gap and relative speed) have different impact on choosing each alternative in next time step. When current speeds are fast enough, drivers prefer to maintain or slow down current speeds. As a result, the probability of choosing alternatives 3 and 2 is higher than that of other alternatives. In order to capture such different attractiveness of each alternative, alternative-specific parameters are used in the model. The observed utility is proposed as,

$$\begin{aligned} V_{int} = {} & C_{in} + \beta_{Ti}(T_n - T_{base}) + \beta_{vi}(v_{nt} - v_{mean}) \\ & + \beta_{Adi} Ad_{nt} + \beta_{LTi}(LT_n - T_{base}) \\ & + \beta_{Gi}(Gap_{nt} - Gap_{mean}) + \beta_{Rvi} Rv_{nt}, \end{aligned} \tag{4.3}$$

where

C_{in} = random-alternative specific constant for vehicle n;

T_n = the type of vehicle n;

T_{base} = the basic vehicle type;

v_{mean} = the mean speed in the data set to be used;

Ad_{nt} = the current acceleration or deceleration of vehicle n;

LT_n = the type of preceding vehicle;

Gap_{mean} = the mean gap in the data set to be used;

Rv_{nt} = the relative speed between the leader and vehicle n.

Furthermore, βs are corresponding parameters needed to be estimated.

It is worth to note that some variables minus reference values are used in the model, such as the vehicle type minus the basic vehicle type, the speed minus the mean speed. In fact, doing this can improve explicability of this model, which will be illustrated in the third section. It is also noted that the vehicle type variable is incorporated in the utility function. Although it is more reasonable to construct different utility functions for different vehicle types, a larger number of parameters that go with different utility functions will definitely limit the applicability of the proposed model.

For the standard logit model, assuming that the unobserved error terms independently and identically belong to Gumble distribution over alternatives, drivers as well as choice situations and following (McFadden 1973), the predicted probability of choosing alternative i in next time step can be computed as,

$$P_{\mathrm{int}} = \frac{e^{V_{\mathrm{int}}}}{\sum_{j=1}^{5} e^{V_{jnt}}}, i = [1, \ldots, 5] \cdot \tag{4.4}$$

However, the assumption of independently distributed error terms prevents a treatment of correlation in errors across alternatives and choice situations for the same driver, and the assumption of identically distributed error terms does not allow for random driving behavior variations in errors across drivers. In order to obviate such limitations, in this study, the mixed logit model is adopted and specify that alternative-specific constants independently belong to normal distribution, $C_i \sim N(\mu_i, \sigma_i^2)$, where μ_i, σ_i are the mean and standard deviation of normal distribution. Let $\xi = (C_1, \ldots, C_5)$, $\alpha = (\mu_1, \ldots, \mu_5)$, $\beta^2 = (\sigma_1^2, \ldots, \sigma_5^2)$. For the proposed mixed logit model, the predicted probability of choosing alternative i in next time step can be calculated as, $P_{\text{int}}^{*} = \int_{\mathbb{R}} P_{\text{int}}(i \mid \xi) N(\alpha, \beta^2) d\xi, i = [1, ..., 5]$. (4.5)

Due to the unclosed form, this model has to be estimated by using simulated maximum likelihood method (Train 2003).

4.3 Data Sets

The trajectory data used in this study were collected on a stretch of interstate freeway I-80 in Emeryville, California, by using several video cameras that were mounted on a nearby high story building. The data sets were provided by Cambridge Systematic Incorporation for Federal Highway Administration as a part of Next Generation Simulation (NGSIM) program. Detailed information of observed vehicles, (vehicle type and size, lane identification, two dimension position, speed and acceleration) were extracted from video data, as well as the information about the preceding and following vehicles. Traffic is composed of three different vehicle types, motorcycle, automobile and truck (denoted as 1, 2 and 3). Fig. 4.2 provides a schematic illustration of the study site. It has five main lanes and one auxiliary lane, and the leftmost lane (lane 1) is a HOV lane.

Data reflecting congested traffic conditions between afternoon peak periods were collected during 5:00-5:30 pm on April 13, 2005. Since only acceleration and deceleration behavior are discussed in this research, in order to avoid interference from lane-changing behavior, trajectory data in the HOV lane are used. Data during 5:00-5:15 pm and 5:15-5:30 pm, denoted as data set 1 and data set 2, are used for model estimation and validation, respectively. Traffic composition and traffic characteristics are presented in Table 4.1, where the mean speed and gap are mean values of instantaneous speed and gap for all vehicles in data set 1 and 2.

In addition, Fig. 4.3 and Fig. 4.4 exhibit the acceleration and deceleration distribution in data set 1 and 2, where values are rounded toward negative infinity. One can see that 99% acceleration and deceleration range from -5 m/s^2 to 5 m/s^2. There also exists a few severe acceleration and deceleration, most of which were conducted by motorcycle drivers.

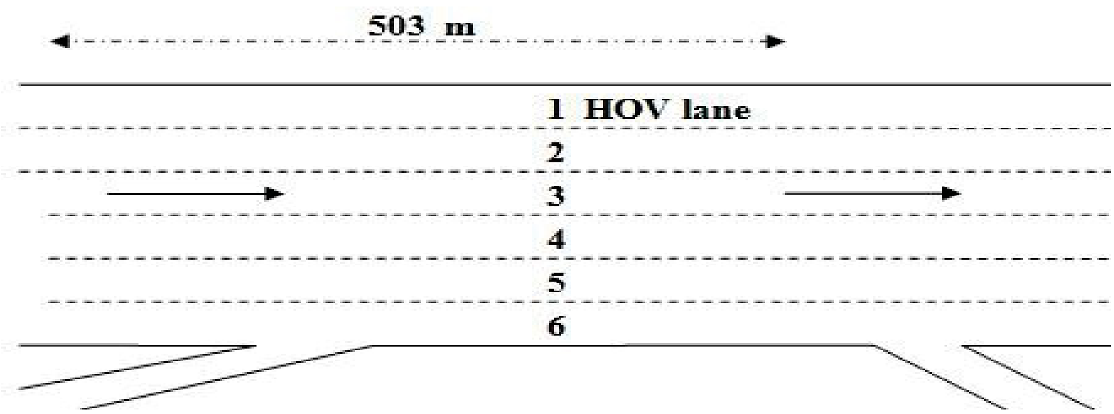

Fig. 4.2 The illustration of the data collection site which is northbound in reality.

Table 4.1 Traffic composition and traffic characteristic in data set 1 and 2.

Data sets	Traffic composition			Traffic characteristics	
	motorcycle	automobile	truck	mean speed	mean gap
Set 1	24	373	15	13 m/s	25 m
Set 2	15	378	13	12 m/s	23 m

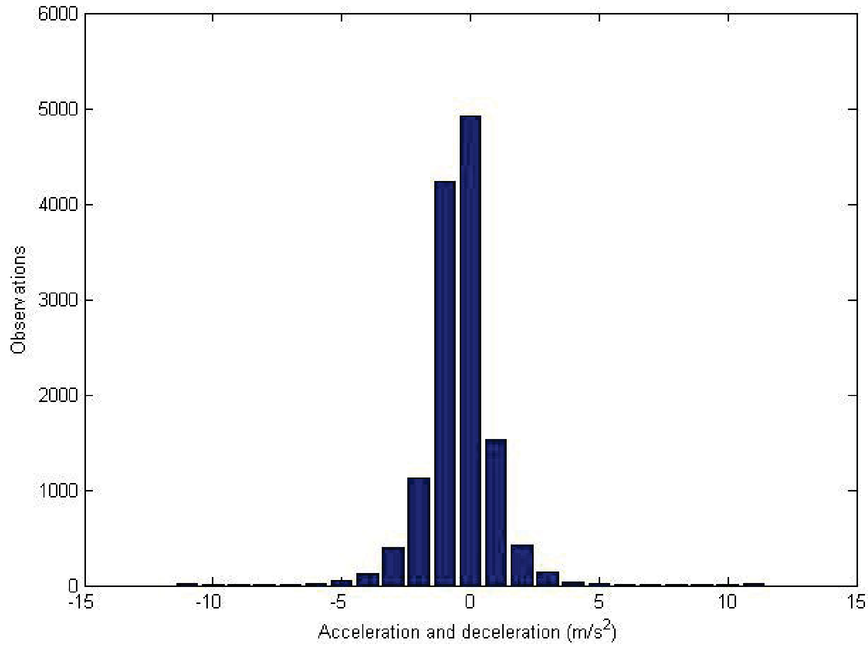

Fig. 4.3 Acceleration and deceleration distribution in data set 1.

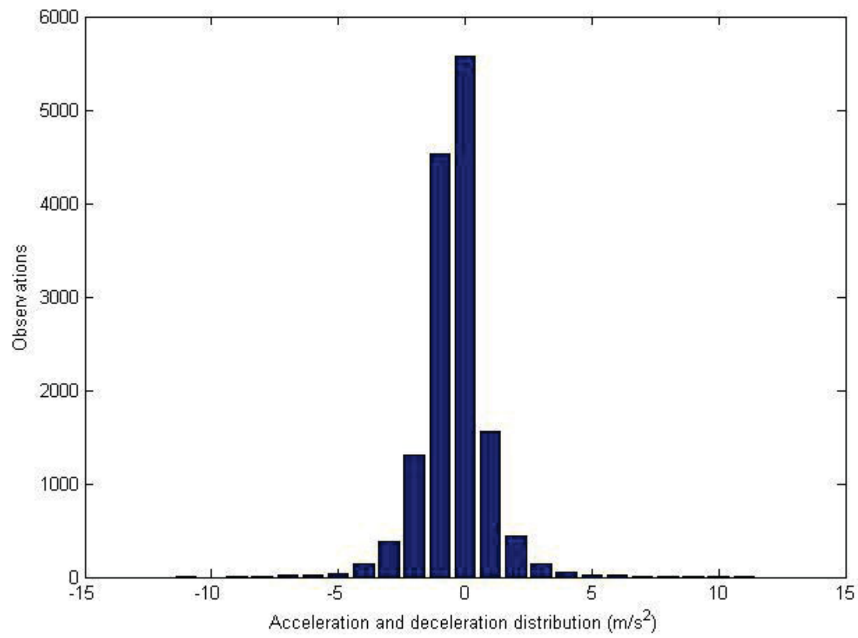

Fig. 4.4 Acceleration and deceleration distribution in data set 2.

4.4 Model Estimation

In this study, based on some study in drivers' reaction delay time (Brackstone and McDonald 1993; Ozaki 1993), the time interval between two successive choices made by drivers is taken as one second. The data set for model estimation includes 13119 observations of 412 vehicles.

Parameters in utility function (3) are estimated by Biogeme (Bierlaire 2003) software and listed in Table 4.2.

Alternative 3 is set as the base for all variables. Automobile is taken as the basic vehicle type, that is, T_{base} = 2. Ma and Md in alternatives are set as 5 m/s^2 and -5 m/s^2, according to Fig. 4.3 and Fig. 4.4.

Table 4.2 The estimation results by using the data set 1.

	Alternative 1		Alternative 2		Alternative 4		Alternative 5	
Parameter	Value	t-test	Value	t-test	Value	t-test	Value	t-test
C_{μ}	-4.65	-45.03	-2.22	-49.54	-1.69	-58.85	-4.24	-47.59
C_{σ}	-0.03	0*	0.37	6.47	0.08	0.56*	0.01	0*
β_T	0	0*	0.39	3.07	-0.44	-4.08	-0.66	-2.28
β_v	0.18	6.73	0.13	9.00	-0.01	-0.88*	-0.08	-2.69
β_{Ad}	0.46	13.06	0.28	12.28	0.04	1.85*	-0.32	-8.47
β_{LT}	-0.03	-0.09*	-0.31	-2.45	0.17	1.96	0	0*
β_G	-0.03	-6.76	-0.03	-9.00	0.01	4.76	0.03	7.45
β_{Rv}	-0.57	-19.00	-0.43	-24.25	0.25	17.89	0.35	13.17

Number of vehicles: 412	Number of observations: 13119
Init log-likelihood: -21059.34	Final log-likelihood: -10873.34
Likelihood ratio test: 20371.99	**Rho-square: 0.484**

* means the estimated parameters are not significantly different from zero at 99% confidence level.

From Table 4.2, one can see that there are some parameters which are not significantly different from zero at 99% confidence level and marked by *.

For random constants, with large t-values, the means of normal distribution are significantly different from zero. However, important differences with zero are not observed in standard deviations, except for the one in alternative 2. It implies random driving behavior variations across drivers reflected by constant term are not significant in the used data set.

For trucks whose value of vehicle type difference is T_n - T_{base} = 3 - 2 = 1, the parameters of vehicle type difference in alternative 4 and 5 are negative. It means truck drivers do not prefer to acceleration alternatives, especially for maximum acceleration alternative, in the used data set. On the contrary, for motorcycles whose value of vehicle type difference is -1, it seems alternatives 4 and 5 are more preferable than other alternatives. This is reasonable since differences in maneuverability and the vehicle type make truck drivers cautious and motorcycle drivers aggressive.

When current speeds are faster than the mean speed, drivers prefer to use deceleration to slow down in next time step, according to the parameters of the speed difference variable. Based on the parameters of the acceleration and deceleration variable, alternatives 1 and 2 are more likely to be selected for vehicles under acceleration. We also note that for parameters of the speed difference and acceleration and deceleration variable, the difference between alternatives 3 and 4 is tiny.

From parameters of the preceding vehicle type difference, it shows that the difference in choosing alternatives 1, 3, and 5 is not notable. This may result from small number of motorcycles and trucks, relative to the number of automobiles in the used data set.

Although magnitudes of gap difference parameters are small, they have relative large t-values, which reflect sensitivity of this variable. By parameters, it shows that when current gaps are greater than the mean gap, alternatives 5 and 4 have higher chosen probabilities, compared to alternatives 1 and 2.

According to common driving experiences, when preceding vehicles are slower than following vehicles, the drivers in following vehicles have to be cautious in avoiding collision with preceding vehicles and intend to decelerate to maintain desired gaps. On the other hand, when leader's speeds are faster than following vehicles speeds, even with small gaps, the drivers of following vehicles are also likely to accelerate to follow the leaders. This driving behavior is realistically represented by the parameters of the relative speed variable. Predicted probabilities for choosing alternatives 5 and 4 are relative higher than that for choosing alternatives 1 and 2, when preceding vehicles are faster than following vehicles.

From above analysis, one can see that estimated parameters in Table 4.2 demonstrate reasonability of the proposed model. In addition, it is important to note that variables minus reference values used in utility function (3) make corresponding parameters more explainable.

4.5 Model Validation

While reasonability of the proposed model is demonstrated through estimated parameters in the previous section, accuracy of this model still needs to be validated. Two data sets are adopted for model validation: data set 1 used for model estimation and data set 2 which is not involved in estimation process and includes 14292 observations of 406 vehicles. For the proposed model, parameters in Table 4.2 marked by * are set to zero.

Firstly, we apply the estimated model to predict the probabilities of choosing each alternative in the next time step for every observation in data sets 1 and 2. Fig. 4.5 presents the distribution of predicted probabilities for chosen alternatives in next time step in data sets 1 and 2.

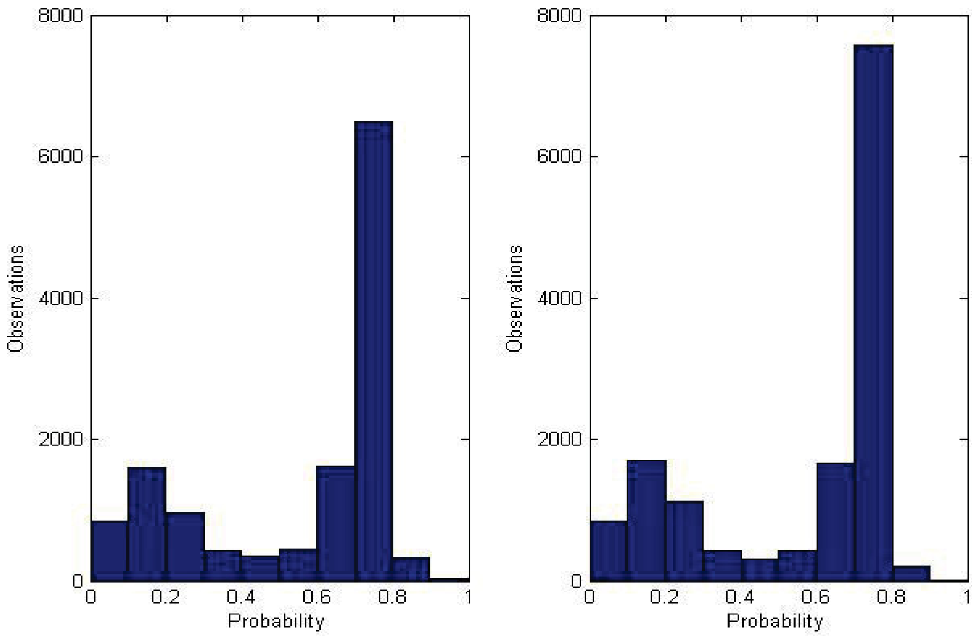

Fig. 4. 5 Distribution of predicted probabilities of chosen alternatives in data set 1 (the left) and 2 (the right).

From Fig. 4.5, we can see that predicted probabilities of chosen alternatives between 70% and 80% are most prominent both in data sets 1 and 2. In addition, the percentage for predicted probabilities of chosen alternatives which are more than 20% (the average probability of choosing each alternative) in data set 1 and data set 2 are 81.34% and 82.13%, respectively, and for predicted probabilities of chosen alternatives which are more than 50% are 67.98% and 69.17%, separately. By these figures, it indicates that accuracy of the proposed model is sufficiently confirmed.

Furthermore, it is worth to note that the model performs better in data set 2 than in the data set used for estimation, which shows strong robustness of the estimated model.

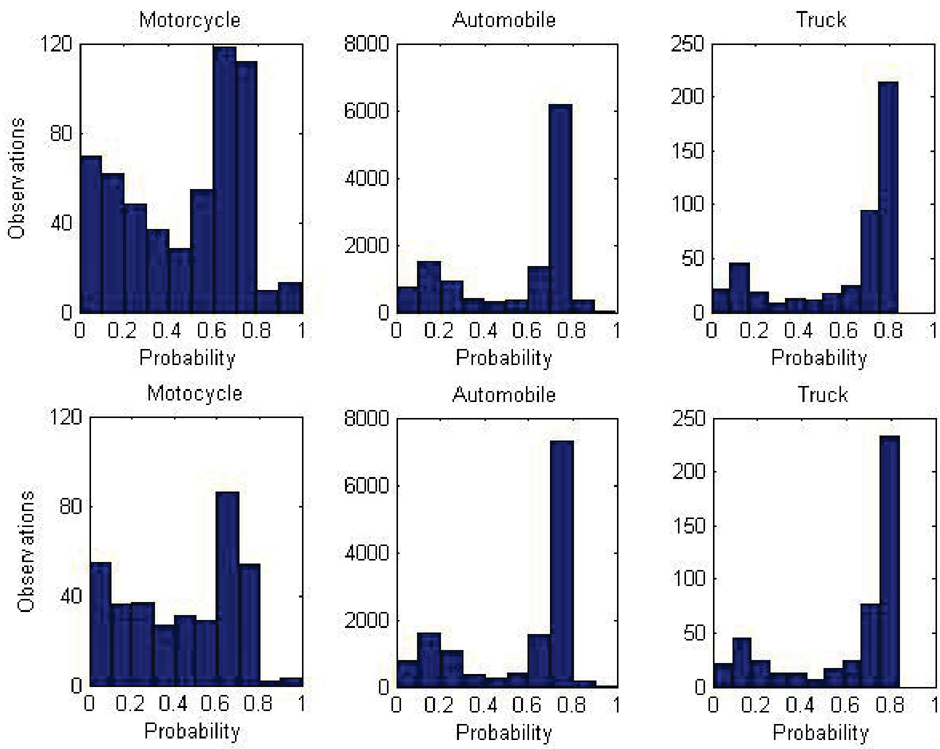

Fig. 4.6 Distribution of predicted probabilities of chosen alternatives for different vehicle type in data set 1 (the upper) and 2 (the lower).

In Fig. 4.6, the distribution of predicted probabilities of chosen alternatives for different vehicle types in data sets 1 and 2 are provided. Obviously, predicted results for motorcycles are not satisfactory, relative to that of automobiles and trucks. However, this is reasonable. As is well known, with high maneuverability and small size, motorcycle drivers seem to be more aggressive. In fact, in the used data sets, there are some motorcycle drivers driving at rather small gaps and even passing preceding vehicles along the edge of HOV lane. Such aggressive driving behavior of motorcycle drivers reduces accuracy of the estimated model, to some extent.

In what follows, we validate the model from other perspective. For the observation k of driver n, let y_{ink} = 1 if alternative i is selected in the next time step, otherwise 0, and denote the predicted probability of choosing alternative i as P_{ink}, i = [1, ..., 5]. Then, the following fact can be given,

$$\sum_{i=1}^{5}\sum_{n=1}^{N}\sum_{k=1}^{K_n} y_{ink} = \sum_{i=1}^{5}\sum_{n=1}^{N}\sum_{k=1}^{K_n} P_{ink} = M, \tag{4.6}$$

where K_n, M are the number of observations for driver n and the number of total observations .

If $\sum_{n=1}^{N}\sum_{k=1}^{K_n} P_{ink} = \sum_{n=1}^{N}\sum_{k=1}^{K_n} y_{ink}$ for each alternative i, one can say that the model can accurately predict the shares of observations.

From Fig. 4.7, as expected, the predicted shares are similar to the observed, which also illustrates accuracy of the proposed model.

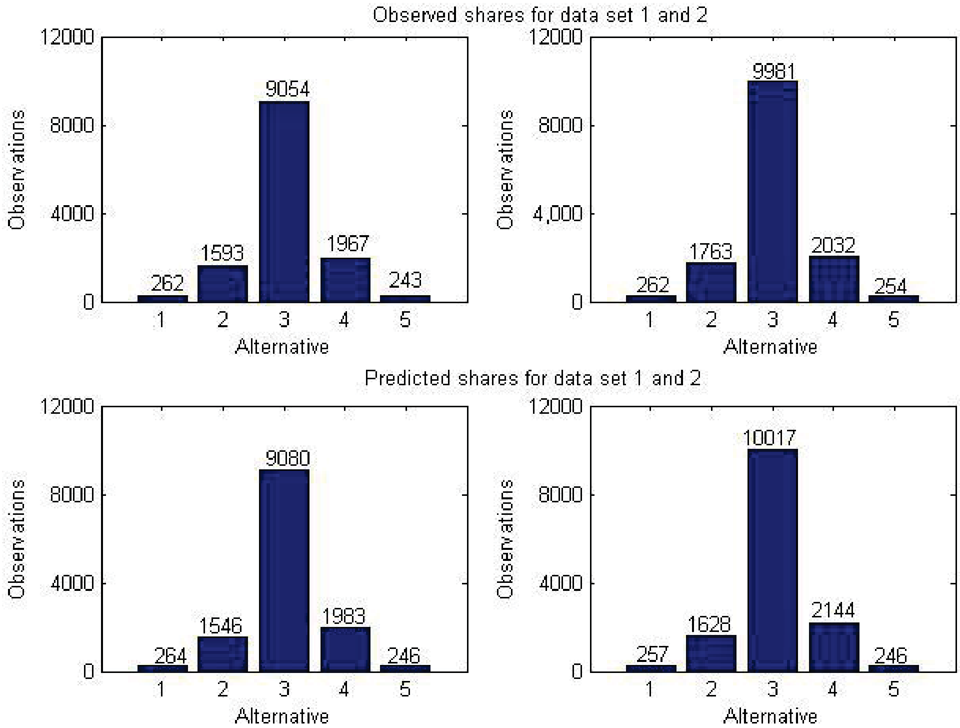

Fig. 4.7 The observed and predicted shares for data sets 1 and 2.

4.6 <u>Simulation</u>

Although the accuracy of the proposed model is sufficiently validated in the preceding section, we believe that there is no better way to validate the model than to apply it to simulate real traffic, since the purpose of developing traffic model is to simulate unknown traffic conditions. In fact, some problems in the model are found with the help of simulation.

Fig. 4.8 shows the flowchart of simulation process. Firstly, drivers judge the availability of each alternative in next time step, according to current traffic conditions. Then, the proposed model is applied to estimate the probability of choosing each available alternative. Subsequently, according to the corresponding probabilities, one alternative is determined at random. Here, it is important to point out that: the alternative with the highest predicted probability may not be definitely selected in this step; It just has the highest probability of being chosen. This is consistent with the definition of probability, and introduces randomness into simulation. In vehicle movement step, similar to cellular automata model (Nagel and Schreckenberg 1992), we introduce some assistant mechanisms to limit unreasonable speed and avoid collision.

Vehicle movement:

$$\tilde{v}_n(t+1) = \max\{V_{\min}, v_n(t) + AD_i\}, \tag{4.7}$$

$$\tilde{v}_n(t+1) = \min\{\tilde{v}_n(t+1), V_{\max}\}, \tag{4.8}$$

$$v_n(t+1) = \min\{\tilde{v}_n(t+1), Gap_n(t) - C_{gap}\}, \tag{4.9}$$

$$x_n(t+1) = x_n(t) + v_n(t+1), \tag{4.10}$$

where $\tilde{v}_n$ is the temporary value, V_{min}, V_{max} are the minimum and maximum speed in the used data. AD_i is the acceleration or deceleration relating to the chosen alternative i.

One-hour single-lane traffic conditions are simulated. Traffic flow is set as 1636 veh/hour, which is composed of 78 motorcycles, 1502 automobiles and 56 trucks. Vehicles are generated at random and initial speeds are set as the mean speed of the used data sets in the simulation run. Data associated with vehicles pasting the specified 503-meter interval in the last 30-minute simulation time are collected to compare with the real traffic conditions composed of data sets 1 and 2. In addition, the following results are the average of five simulation runs and simulation is carried out with MATLAB.

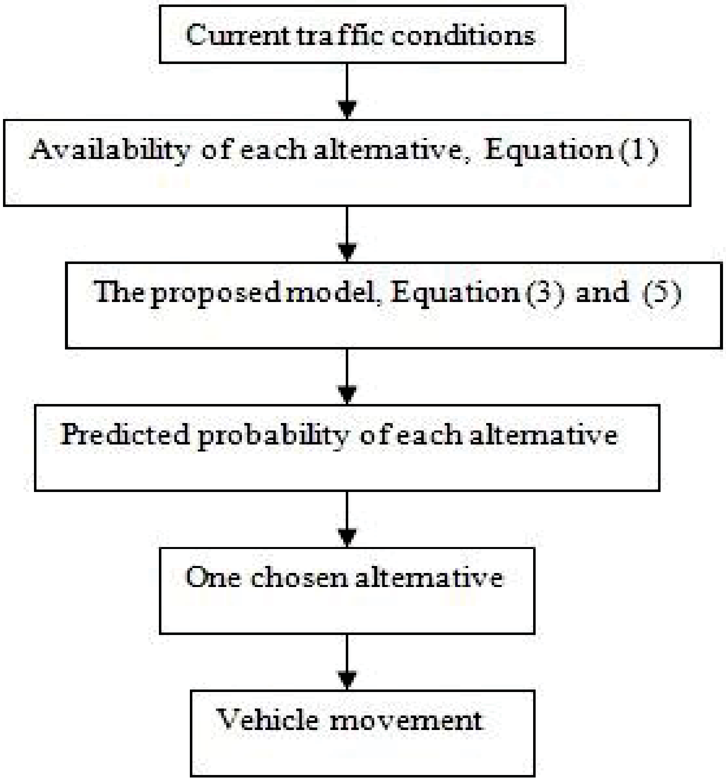

Fig. 4.8 Flowchart of the simulation process.

Table 4.3 The observed and simulated results for different vehicle types.

	Motorcycle	Auto	Truck
	Observed results		
Number	39	751	28
Mean speed	14.6 m/s	12.6 m/s	12.4 m/s
Mean gap	14.9 m	23.9 m	36.7 m
	Simulated results		
Number	38	755	32
Mean speed	9.5 m/s	9.0 m/s	8.6 m/s
Mean gap	17.7 m	19.7 m	27.1 m

Before analyzing the simulation results, importantly, we point out that although assistant mechanisms (Equations. (7-9)) are introduced in the proposed model, in the 3600-second simulation process of 1636 vehicles, the mechanisms are used only 570 times. It implies that the following simulation results largely rely on the proposed model rather than assistant mechanisms.

As an important feature, we firstly check the ability of describing driving differences of different vehicle types for the proposed model. The comparison results for different vehicle types are exhibited in Table 4.3. Number in Table 4.3 is the number of vehicles passing the identified 503-meter study site in 30 minutes, for each vehicle type.

From Table 4.3, we can see that, traffic composition in simulated traffic conditions is similar to that in real traffic conditions, which indicates that simulation is feasible by using the proposed model. Furthermore, it is important to note that the proposed model can represent different driving behavior of different vehicle types. Namely, motorcycle drivers drive at the fastest speeds and smallest gaps; on the contrary, truck drivers drive at the lowest speeds and greatest gaps both in real and simulated traffic conditions.

However, we also note that simulated mean speeds for all vehicle types are lower than the observed ones, and simulated mean gaps except for motorcycle are less than the observed. The reason can be clearly explained by the following vehicle trajectory figures.

In order to check the performance of the proposed model from the microscopic point of view, trajectories in five minutes of the observed and simulated vehicles are presented in Fig. 4.9 and Fig. 4.10.

From Fig. 4.9 and Fig. 4.10, we can see that, on the whole, simulated speeds are lower and simulated speed fluctuations are much severer than the observed results. And, many severe shock waves emerge in the simulation results. Like the real conditions, however, there are no obvious congestions in simulation. As can be seen, Fig. 4.9 and Fig. 4.10 completely reveal the defects of proposed model in simulation process, and also point out the direction of improving this model.

In our view, there are some reasons causing the unrealistic simulated results. First, although we use the data in HOV lane to intentionally avoid interference of lane-changing behavior on acceleration and deceleration behavior; in fact, there are many vehicles changing into or out the HOV lane during data collection time. And, as shown in Fig. 4.7, the aggressive driving behavior of motorcycle drivers is hardly represented by the proposed model. Furthermore, as for the structure of the proposed model, we believe that the discrete nature makes speed fluctuations over severe. And, the fixed reaction delay time for all drivers of different vehicle types in this study may be one reason to the severe shock waves.

Classifying acceleration and deceleration into more than five alternatives can be an effective way to mitigate severe speed fluctuation. However, it also imposes additional burden on calculation, especially for model estimation. Adopting the variable reaction delay time for different drivers of different vehicle types may be a good solution to the severe shock wave phenomena emerging in the simulation results. Besides, more reasonably defining the availability of alternatives, Equation (4.1), may be able to limit unreasonable speed and avoid collision in simulation process, rather than using Equations (4.7-4.9).

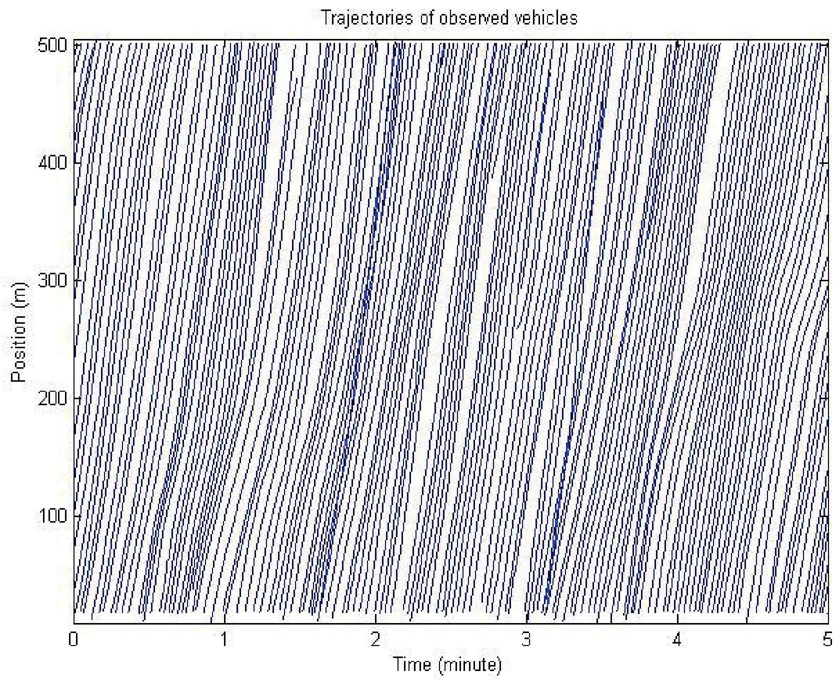

Fig. 4.9 Trajectories of observed vehicles from 5:05 to 5:10.

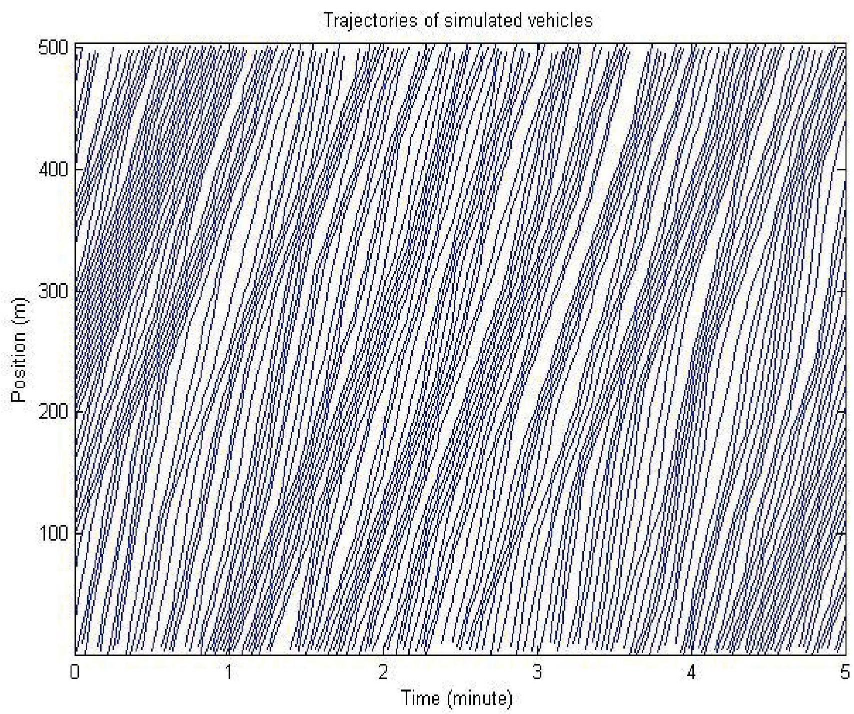

Fig. 4.10 Trajectories of simulated vehicles from the 35th to 40th minute.

4.7 Discussion

Although careful considerations were given in this study, there remain some issues that require further discussions. The main assumption about the driver's decision-making process was not theoretically or empirically verified, as well as the approach used to classify deceleration/acceleration regions. In fact, to validate the reasonableness of the approach of classifying deceleration/acceleration regions, in the following study (Zheng et al. 2012) we tried to classify deceleration/acceleration regions into seven alternatives. From the Rho-square in Table 4.4 in (Zheng et al. 2012), the accuracy of the model declines greatly when deceleration/acceleration regions are divided into seven alternatives. Besides, compared with the 5-min trajectories, the stability of traffic flow are also not improved obviously. Therefore, the reasonableness of the approach of classifying deceleration/acceleration regions into five alternatives has been confirmed.

Table 4.4 Estimation results in (Zheng et al. 2012)

Parameter	D_3		D_2		D_1		A_1		A_2		A_3	
	Value	*T-test*	*Value*	*T-test*	*Value*	*T-test*	*Value*	*T-test*	*Value*	*T-test*	*Value*	*T-test*
C_i	-5.03	-24.43	-2.40	-38.37	-0.39	-14.8	-0.16	-6.47	-1.89	-41.2	-4.21	-28.01
β_{vi}	6.20	8.98	3.36	12.75	1.34	9.55	-0.05	0.35*	-0.89	-3.57	-4.05	-5.60
β_{Adi}	0.48	6.86	0.21	4.81	-0.06	-2.59	0.16	6.47	0.21	4.54	-0.09	-2.91
β_{Gapi}	-1.90	-4.71	-1.34	-8.44	-0.58	-7.10	0.37	5.09	0.89	6.61	1.22	3.29
β_{Rvi}	-0.54	-2.85	-0.80	-10.96	-0.46	-12.91	0.20	6.03	-0.09	1.44*	-0.44	-2.65

Number of vehicles: 376	Number of observations: 11509
Init log-likelihood: -22321.74	Final log-likelihood: -15795.83
Likelihood ratio test: 13051.83	Rho-square: 0.292

4.8 Conclusions

In this study, a mixed logit model is proposed to describe drivers acceleration and deceleration behavior. Acceleration and deceleration are discretized into five alternatives. To represent different attractiveness of each alternative, alternative specific parameters are adopted in the model. Moreover, variables minus reference values are used, which improve explicability of the proposed model. Driving differences of different vehicle types are taken into account by the vehicle type variable in the model. In order to avoid interference of lane-changing behavior, this model is estimated and validated by trajectory data in HOV lane. The estimated parameters show reasonability of this model, and validation results sufficiently demonstrate robustness and accuracy of the model. Finally, the model is applied to simulate 30-minute traffic conditions. Simulation results exhibit that this model can describe driving differences of different vehicle types. Meanwhile, defects of this model in simulation process are also disclosed.

For further research, this model can be extended along two directions, in our view. In this study, we attempt to use the random alternative-specific constants to capture driving behavior variations across drivers. However, estimated results show that, except for the alternative 2, standard deviations of the specified normal distribution are not significantly different from zero. This means the proposed model is similar to the standard logit model. This model may be extended to capture such variations through specifying other random terms or a mixed error term (Bhat and Gossen 2004). Furthermore, lane-changing behavior can be integrated in the model by defining alternatives as in study (Antonini et al. 2006; Robin et al. 2009). We believe that each of the extensions of this model is a compelling and promising work.

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CHAPTER 5. CAR-FOLLOWING BEHAVIOR WITH INSTANTANEOUS DRIVER-VEHICLE REACTION DELAY: A NEURAL-NETWORK-BASED METHODOLOGY

5.1 Introduction

Due to the ability of capturing the complexity of traffic systems, traffic simulation has become one of the most used approaches for traffic planning, traffic design and traffic management. A wide variety of traffic simulation software is currently available on the market and is utilized by thousands of consultants, researchers and public agencies (Barceló 2010; Bloomberg and Dale 2000; Hidas 2005; Takahashi et al. 2002; Wu et al. 2003; Yang and Koutsopoulos 1996). With the popularity of traffic simulation, the car-following and lane-changing models, two of the most significant components in traffic simulation, have naturally attracted a lot of attention from traffic researchers (Brackstone and McDonald 1999; Gipps 1986; Hidas 2002; Panwai and Dia 2005; Toledo 2007; Zheng et al. 2012a). A number of models have been proposed in the past decades to describe such driving behavior more realistically and accurately.

The concept of car following was first proposed by Reuschel (1950) and Pipes (1953), which assumed that the following vehicle controls its behavior with respect to the preceding vehicle in the same lane. Thereafter, considerable car-following models were developed to mimic this behavior more consistently with real traffic. In (Gipps 1981), equations of motion were accepted to describe driver's acceleration and deceleration behavior. According to stimulus and response relationship, Gazis et al. (1961) proposed a widely studied car-following model. Kikuchi and Chakroborty (1992) built a car-following model based on fuzzy logic theory. In addition, Nagel and Schreckenberg (1992) presented a typical cellular automata model to simulate vehicle movements. And, the model formulation in (Bham and Benekohal 2004) adopted the concept of cellular automata and car-following models. Besides, neural networks were also used to model car-following behavior (Panwai and Dia 2007). Based on discrete choice theory, drivers' acceleration and deceleration decisions were evaluated (Zheng et al. 2012b; Zheng et al. 2012c).

Reaction delay is a common characteristic of humans in operation and control, such as driving a car. The operational coefficients and delay characteristics of humans can vary rapidly because of changes in factors such as task demands, motivation, workload and fatigue. As mentioned above, research on car-following models historically has focused on exploration of different modeling frameworks and variables that affect this behavior. Recently, researchers have recognized that reaction delay of each driver is an indispensable factor for the identification of car-following models since it affects traffic dynamics not only in a microscopic way but also macroscopically (Ma and Andréasson 2006). However, due to that the estimation of variations in reaction delay is almost impossible in classic paradigms, in the abovementioned car-following models reaction delay was all assumed to be fixed. Besides, in previous studies the delay within the mechanical system of a vehicle was usually neglected. In fact, the time that a vehicle takes to respond to a request (decelerating, accelerating, steering) depends greatly on the vehicle and roadway conditions, and is different for different types of vehicles (motorcycle, car, heavy vehicle). For modeling vehicle movements more realistically, vehicle reaction delay should also be considered.

As an effort to circumvent the limitations to modeling vehicle movements, by defining the time interval between the relative speed and acceleration observed in real traffic as reaction delay, Khodayari et al. (2012) proposed a neural-network-based car-following model which can take instantaneous driver-vehicle reaction delay into consideration. Although based on their method for some vehicles driver-vehicle reaction delay can be clearly identified, an explicit reaction delay model was not presented in the research, which completely limits the applicability of the method in simulation.

In this study, the driver-vehicle reaction delay is specified by the time interval not only between the relative speed and acceleration but also between the gap and speed of the vehicle. A neural network for instantaneous reaction delay is trained by observed delay samples and then compared with a previous piecewise linear reaction delay model. Comparison results show that the neural network delay model is more realistic than the piecewise linear model. Incorporating the reaction delay network into a neural-network-based car-following model, movements of nine vehicles which follow each other are simulated. Simulation results demonstrate that the models with instantaneous driver-vehicle reaction delay clearly outperform the models with fixed reaction delay. Furthermore, the model with short fixed reaction delay makes the simulated vehicles follow each other more closely than the observed vehicles do, and collisions happen in the model with long fixed reaction delay, which also indicates that taking instantaneous reaction delay into account is essential for modeling vehicle movements.

The paper is composed of five sections. Data sets used in this study are briefly introduced in the subsequent section, followed by the description of the neural-network-based methodology. In Section 5.4, the proposed methodology is thoroughly validated. The last section is devoted to the conclusions.

5.2 Data sets

The data used in this study were collected on a segment of U.S. Highway 101 in Los Angeles, California, by using eight video cameras that were mounted on a high story building. The study site is 640 meters long and covers an on-ramp and an off-ramp. There are five mainline lanes throughout the study site and an auxiliary lane is present through a portion of the corridor between the on-ramp and the off-ramp. The data sets were provided by Cambridge Systematic Incorporation for Federal Highway Administration as a part of the Next Generation Simulation (NGSIM) program. Detailed information about observed vehicles, (vehicle type and size, lane ID, two-dimension position, speed and acceleration) was extracted from video data, together with information about the preceding and following vehicles.

Table 5.1 Traffic composition and traffic flow characteristics

Number of automobiles	Number of heavy vehicles	Number of motorcycles
5919 (97.0%)	137 (2.2%)	45 (0.7%)
Flow rate (veh/hr)	Average speed (km/hr)	Density (veh/km)
8077	35.0	231

Data reflecting congested traffic conditions in morning peak periods were collected during 7:50 am and 8:35 am on June 15, 2005. Traffic composition and traffic flow characteristics are listed in Table 1. In addition, the data were collected in clear weather, good visibility, and dry pavement conditions. A detailed analysis of the data and the data processing methodology is presented in NGSIM U.S. 101 Data Analysis Report (Cambridge Systematics Inc. 2005).

Besides, in order to alleviate the noise in the data (Punzo et al. 2011), the moving-average filter for a duration of one second is applied to all vehicle trajectories before data analysis in this study.

5.3 The neural-network-based methodology

The methodology is based on two models, the reaction delay model and the car-following model. As displayed in Fig. 1, according to traffic conditions (speed, gap, relative speed, ...) at time *t*, the reaction delay model is used to estimate the time ΔT that is required for the reaction of the driver-vehicle unit. On the other hand, the car-following model is applied to calculate the speed that the driver is going to accelerate/decelerate to in the next step. With respect to the driver-vehicle reaction delay, the expected speed can only be reached at $t+\Delta T$, denoted by $v(t+\Delta T)$. In addition, to reflect continuous change in speed, we set the speed between t and $t+\Delta T$ as,

$$v(t+k) = v(t) + k \times \frac{v(t+\Delta T) - v(t)}{\Delta T},\ k \in [t_0, 2t_0, ..., \Delta T), \tag{5.1}$$

where t_0 is the minimum time step in simulation.

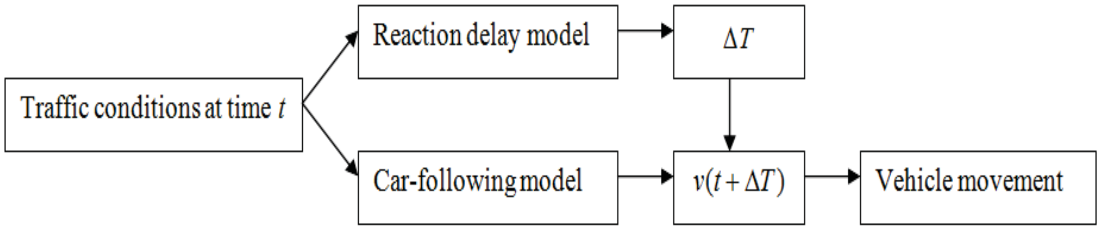

Fig. 5.1 Conceptual operation of the proposed methodology.

In this study, the proposed reaction delay and car-following models are all based on neural networks. We will briefly introduce neural networks and the back-propagation algorithm for network training in the next subsection.

5.3.1 Neural networks and the back-propagation algorithm

Since 1990s, there has been an increased interest concerning artificial neural networks in a wide variety of disciplines (Adeli 2001; Dougherty 1995; Kalogirou 2000; Kalyoncuoglu and Tigdemir 2004; Karlaftis and Vlahogianni 2011; Rafiq et al. 2001; Sinha and McKim 2000). Typically, two advantages contribute to the popularity of neural networks. One advantage is that neural networks are able to handle noisy data and approximate any degree of complexity in non-linear systems (Adeli 2001; Kalogirou 2000; Rafiq et al. 2001). Another advantage is that, they do not require any simplifying assumptions or prior knowledge of problem solving, compared with statistical models (Kalyoncuoglu and Tigdemir 2004; Karlaftis and Vlahogianni 2011). For example, in regression models we have to specify the underlying relationship (linear, polynomial, exponential, rational ...) between independent and dependent variables before model estimation. However, such specification is not necessary for inputs and outputs in neural networks. In terms of the topic discussed in this study, driver-vehicle reaction delay and car following are two complicated concepts. Although there are some findings in previous studies, it is not clear what factors impact the reaction delay and car-following behavior, and what their underlying relationships are. Therefore, by virtue of the abovementioned features we believe that neural networks are more flexible than statistical approaches. In fact, validation results in Sec. 5.4 also confirm our judgment.

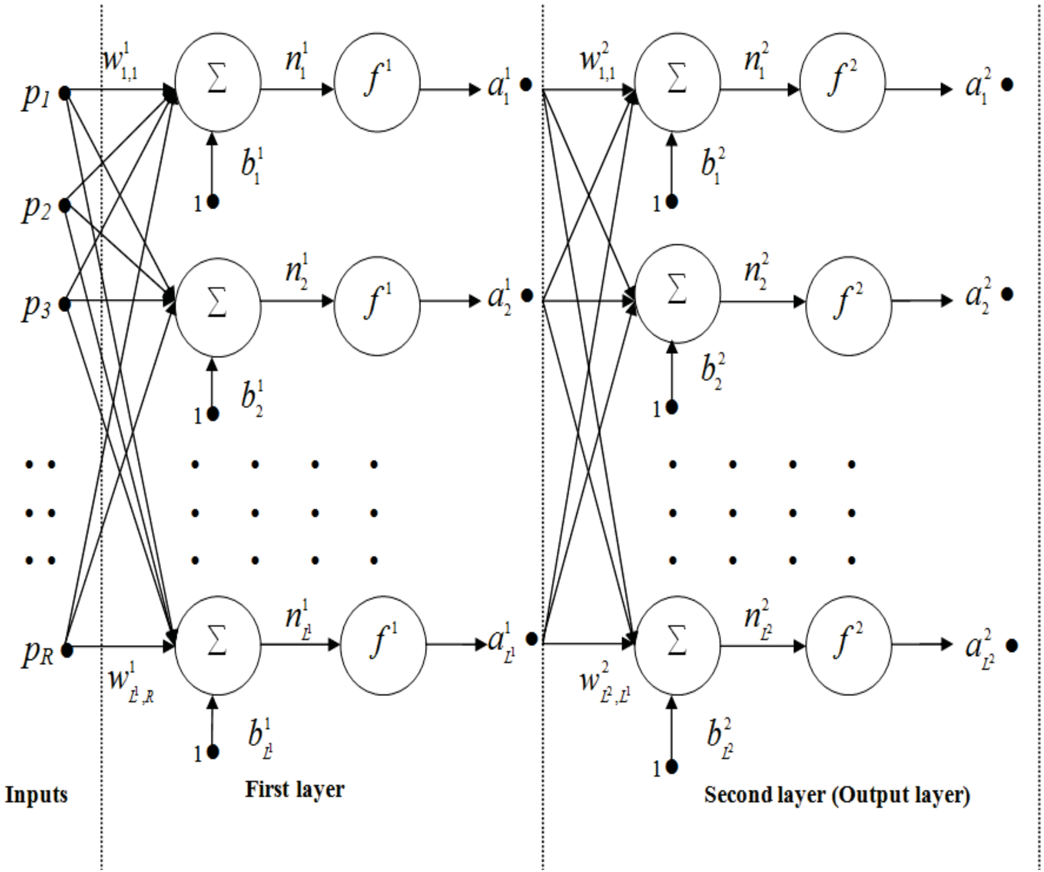

Fig. 5.2 The schematic diagram of a two-layer feed-forward neural network.

According to (Haykin 1999), a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: the knowledge is acquired by the network through a learning process, and inter-neuron connection strengths, known as synaptic weights, are used to store the knowledge. A schematic diagram of a typical multilayer feed-forward neural network is displayed in Fig. 5.2.

Before describing the neural network, it is important to give an explanation about superscripts and subscripts used in notations. In this study, we use superscripts to denote layers and subscripts to represent neurons. The first subscript refers to the neuron in question and the second subscript stands for the source of the signal fed to the current neuron.

The network is composed of inputs and two layers. The last layer of a neural network is also called the output layer. The input vector consists of R elements $p_1, p_2, ..., p_R$. Each input element p_i is multiplied by a weight $w_{j,i}^1$ to form $w_{j,i}^1 p_i$, one of the terms that is sent to the summer. The other input, the constant 1, is multiplied by a bias b_j^1 and then passed to the summer. The summer output $n_j^1 = \sum_{i=1}^{R} w_{j,i}^1 p_i + b_j^1$, often referred to as the net input, goes into the transfer function f^1, which produces the neuron output a_j^1 in the first layer. The bias b_j^1 has the effect of increasing or lowering the net input of the transfer function, depending on whether it is positive or negative, respectively. L^1 is the number of neurons adopted in layer one.

If we relate the artificial neural network to a biological neuron, the weights and bias $w^1_{j,i}$, b^1_j correspond to the strength of a synapse. A cell body is represented by the summer and transfer function, and the neuron output a^1_j represents the signal on an axon.

In the same way, treating the outputs of layer one as the inputs of layer two, the signals from layer one are passed through layer two. The transfer function in layer two f^2 can be totally different from that in the first layer. The outputs of layer two, $a^2_k,\ k \in [1,2,...,L^2]$, are also the outputs of the discussed neural network. L^2 is the number of neurons used in layer two.

The neuron network can also be written in the following matrix form:

$$a^1 = f^1(\mathrm{W}^1\, p + b^1),\ a^2 = f^2(\mathrm{W}^2\, a^1 + b^2) \tag{5.2}$$

where W^1, W^2 are the weight matrixes and p, b^1, b^2, a^1, a^2 denote the input, bias and output vectors in layers one and two.

The property that is of primary significance for a neural network is the ability of the network to learn from its environment, and improve its performance through learning. In the context of neural networks, learning is defined as a process by which free parameters (weights and biases) of a neural network are adapted through a process of stimulation by the environment in which the network is embedded. The network uses a learning mode, in which inputs are presented to the network along with the desired outputs and parameters are adjusted so that the network attempts to produce the desired outputs.

The back-propagation algorithm is one of widely used learning methods for multilayer neural networks. The back-propagation algorithm attempts to improve neural network performance by reducing the total error through changing the gradient weights and biases. The mean square error is often used as a measure of neural network performance,

$$E = \frac{1}{M}\sum_{m=1}^{M}\sum_{k=1}^{L^2}(r_k(m) - a_k^2(m))^2 \tag{5.3}$$

where r_k is the actual output and M is the number of samples in the training data set.

The parameter change for neurons in layers one and two can be respectively denoted as,

$$\Delta w_{j,i}^1 = -\eta\frac{\partial E}{\partial w_{j,i}^1}, \Delta b_j^1 = -\eta\frac{\partial E}{\partial b_j^1}, i \in [1,2,...,R], j \in [1,2,...,L^1], \tag{5.4}$$

$$\Delta w_{k,j}^2 = -\eta\frac{\partial E}{\partial w_{k,j}^2}, \Delta b_k^2 = -\eta\frac{\partial E}{\partial b_k^2}, j \in [1,2,...,L^1], k \in [1,2,...,L^2], \tag{5.5}$$

where η represents the learning rate.

The error signal terms for the jth neuron and the kth neuron in the first and output layers are defined as:

$$\delta_j^1 = -\frac{\partial E}{\partial n_j^1}, \delta_k^2 = -\frac{\partial E}{\partial n_k^2}, j \in [1,2,...,L^1], k \in [1,2,...,L^2]. \tag{5.6}$$

Applying the chain rule, the gradient of the mean square error with respect to weights and biases is as follows, respectively:

$$\frac{\partial E}{\partial w_{j,i}^1} = \frac{\partial E}{\partial n_j^1}\frac{\partial n_j^1}{\partial w_{j,i}^1} = -\delta_j^1 p_i, \frac{\partial E}{\partial b_j^1} = \frac{\partial E}{\partial n_j^1}\frac{\partial n_j^1}{\partial b_j^1} = -\delta_j^1, i \in [1,2,...,R], j \in [1,2,...,L^1], \tag{5.7}$$

$$\frac{\partial E}{\partial w_{k,j}^2} = \frac{\partial E}{\partial n_k^2}\frac{\partial n_k^2}{\partial w_{k,j}^2} = -\delta_k^2 a_j^1, \frac{\partial E}{\partial b_k^2} = \frac{\partial E}{\partial n_k^2}\frac{\partial n_k^2}{\partial b_k^2} = -\delta_k^2, j \in [1,2,...,L^1], k \in [1,2,...,L^2]. \tag{5.8}$$

Furthermore, Eq. 5.6 can be calculated as:

$$\delta_k^2 = -\frac{\partial E}{\partial n_k^2} = -\frac{\partial E}{\partial a_k^2}\frac{\partial a_k^2}{\partial n_k^2} = \frac{2}{M}\sum_{m=1}^{M}(r_k(m) - a_k^2(m)) f^{2\prime}(n_k^2), k \in [1, 2, ..., L^2], \tag{5.9}$$

$$\delta_j^1 = -\frac{\partial E}{\partial n_j^1} = -\frac{\partial E}{\partial n_k^2}\frac{\partial n_k^2}{\partial n_j^1} = \delta_k^2 w_{k,j}^2 f^{1\prime}(n_j^1), j \in [1, 2, ..., L^1]. \tag{5.10}$$

Finally, the weights and biases can be updated using the following equations,

$$w_{j,i}^1(t+1) = w_{j,i}^1(t) + \eta\delta_j^1 p_i, \mathrm{b}_j^1(t+1) = b_j^1(t) + \eta\delta_j^1, i \in [1, 2, ..., R], j \in [1, 2, ..., L^1], \tag{5.11}$$

$$w_{k,j}^2(t+1) = w_{k,j}^2(t) + \eta\delta_k^2 a_j^1, b_k^2(t+1) = b_k^2(t) + \eta\delta_k^2, j \in [1, 2, ..., L^1], k \in [1, 2, ..., L^2]. \tag{5.12}$$

In this study, neural networks are built by using the Neural Network Toolbox and implemented in MATLAB. In the learning process, 70% input samples are used for training and 30 % input samples for model validation. The maximum number of training iterations, the minimum performance gradient, and the learning rate η are set to 1000, 1.0×10^{-5}, and 0.01, respectively.

5.3.2 Definition of driver-vehicle reaction delay

Based on the observed vehicle data, Khodayari et al. (2012) defined the driver-vehicle reaction delay. Fig. 5.3(a) displays the relative speed and acceleration profiles of a vehicle during 100-second recording time. It is clear that, except some time lags, the changing tendency of acceleration is quite similar to that of the relative speed. Treating the relative speed as the stimulus and acceleration as the response, the driver-vehicle reaction delay is defined by the time interval between the relative speed and acceleration, as represented by the arrows in Fig. 5.3(b)

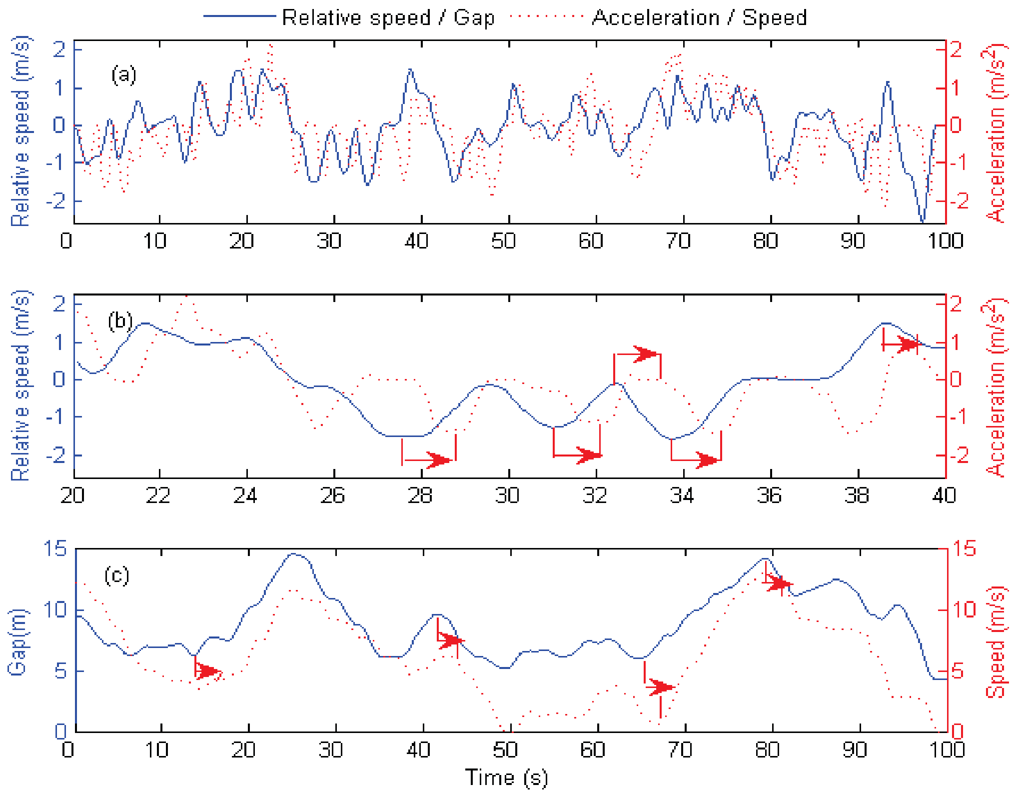

Fig. 5.3 The profiles of the relative speed and acceleration (a, b), the gap and speed (c), for the vehicle closely following its leading vehicle.

According to common driving experience, however, drivers are more likely to adjust their speed based on the current gaps, since the change in the gap is more easily perceived than that in the relative speed. Fig. 5.3(c) displays the gap and speed profiles of the vehicle. We note that the similar changing tendency in the gap and speed is also apparently observed. Besides, for vehicles maintaining large gaps with their leading vehicles, although the correlationship between the relative speed and acceleration is hard to be identified, the time lags between the gap and speed are still apparent, as shown in Fig. 5.4. Therefore, in this study the time interval between the gap and speed is also viewed as the driver-vehicle reaction delay.

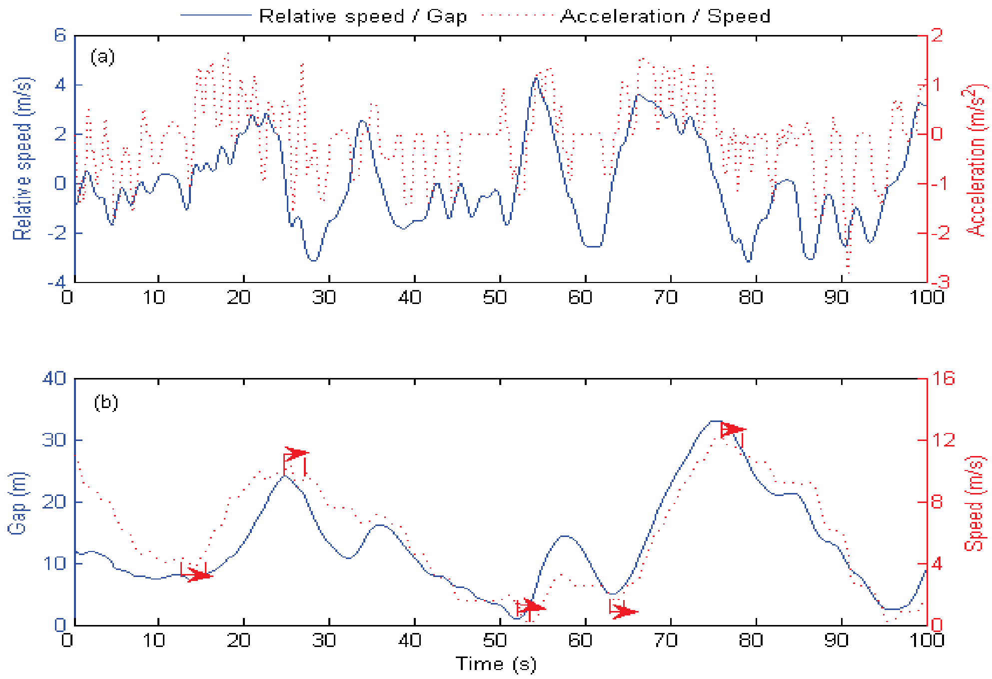

Fig. 5.4 The profiles of the relative speed and acceleration (a), the gap and speed (b), for the vehicle maintaining large gaps with its leading vehicle.

5.3.3 The instantaneous reaction delay model

By the observed time delay between the relative speed and acceleration, as represented by the arrows in Fig. 5.3(b), Khodayari et al. (2012) introduced the driver-vehicle reaction delay. We note that, however, there exist some obvious issues in their research. The most obvious one is that the instantaneous reaction delay model was not explicitly presented. Although for observed vehicles the vehicle movements can be modeled by specifying the reaction delay at some specific time, such as in Fig. 3(b) at the 31st second they can specify the reaction delay as 1 second, for simulated vehicles whose movements in the next time step are totally unknown specifying reaction delay is impossible. Hence, to reflect instantaneous reactive delay in traffic simulation, the instantaneous reaction delay model is essential. Besides, as reaction delay appears to change during a single maneuver of acceleration or deceleration in the car-following behavior, reaction delay is divided into four categories (reaction delay to start deceleration, reaction delay for maximum deceleration, reaction delay to start acceleration, reaction delay for maximum acceleration) in (Khodayari et al. 2012). Similar to the mentioned issue, for observed vehicles such classification is feasible, but for simulated vehicles it is impossible to judge whether the current acceleration/deceleration is maximum or not. Therefore, dividing the reaction delay in four categories is not operational in simulation.

According to the definition of driver-vehicle reaction delay in the previous subsection, 630 reaction delay samples are drawn from 50 cars. The statistic summary is listed in the second row of Table 2. In addition, 4024 car-following samples are also drawn from these cars in order to train the car-following models discussed later.

Considering that reaction delay under acceleration and deceleration is different, Ozaki (1993) proposed a reaction delay model by using a piecewise linear function. The model is recalibrated by the samples in this study, as follows:

$$\Delta T = \begin{cases} 0.743 + 0.016g + 0.037a, & \text{(deceleration)} \\ 0.886 + 0.008g + 0.037a, & \text{(acceleration)} \end{cases} \tag{5.13}$$

where g is the gap and a is the acceleration rate. Hereafter, this model is termed as Ozaki delay.

Although it seems to be reasonable to distinguish between deceleration and acceleration reaction delay, a statistical hypothesis test, Kolmogorov-Smirnov test, shows that such differences are not statistically significant at the 5% significance level in the samples used in this study.

Based on the neural network introduced in Subs. 5.3.1, an instantaneous reaction delay model is developed, which is termed as NN delay in the following discussion. The input elements are the speed, relative speed, acceleration and the gap of the following vehicle. Two layers are adopted in the network. The transfer function in the first layer is Hyperbolic tangent function, written as:

$$f^1(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)}. \tag{5.14}$$

This function is inherently nonlinear and produces outputs with upper and lower bounds, which is considered suitable for complicated systems. Besides, ten neurons are used in the first layer.

The second layer which is also the output layer employs the following transfer function,

$$f^2(x) = \lambda \times \frac{1}{1 + \exp(-x)}, \tag{5.15}$$

where λ is the maximum delay time in the samples. As the output of the neural network is instantaneous reaction delay, only one neuron is included in the output layer.

5.3.4 The car-following model

To reflect the effect of instantaneous reaction delay on simulating real vehicle movements, a car-following model is needed. The car-following model considered in this study is also based on a neural network. Due to that acceleration is derived from observed speed, it is more direct and convenient to model the vehicle speed. Therefore, unlike the models in the previous studies that the dependent variable is acceleration/deceleration (Gipps 1981; Khodayari et al. 2012; Panwai and Dia 2007; Zheng et al. 2012b), the output of the car-following model in this study is the speed of the following vehicle in the next time step.

The inputs are the current speed, relative speed, the gap of the following vehicle and the gap of the leading vehicle. Two layers are employed in the model and the first layer is the same as in NN delay. The transfer function in the second layer is a piecewise linear function, as follows:

$$f^2(x) = \begin{cases} 0, \text{ if } x \le 0; \\ x, \text{ if x} > 0 \end{cases}. \tag{5.16}$$

By using the observed samples, the neural-network-based reaction delay and car-following models are trained by the back-propagation algorithm discussed in Subs. 5.3.1. Besides, in the previous neural-network-based studies (Khodayari et al. 2012; Panwai and Dia 2007), the frameworks of their research were introduced in detail, but the parameters of the proposed neural networks that contain meaningful information about the problems in question were not presented, which makes their results unduplicated. To some extent, this retrains the effective dissemination of their research. In this study, for future reference, the calibrated weights and bias of the reaction delay and car-following neural networks are listed in Appendix.

5.4 Validation of the methodology

Two measures are employed to validate the proposed methodology. One measure is the mean square error, Eq. 3. Another measure is the correlation coefficient between observed and simulated values, defined as follows:

$$R = \frac{\sum_{m=1}^{M}(OV_m - \overline{OV})(\mathrm{S}V_m - \overline{SV})}{\sqrt{\sum_{m=1}^{M}(OV_m - \overline{OV})^2}\sqrt{\sum_{m=1}^{M}(\mathrm{S}V_m - \overline{SV})^2}} \tag{5.17}$$

where $OV_m, \mathrm{S}V_m$ are the observed and simulated values of the sample *m* and $\overline{OV}, \overline{\mathrm{S}V}$ are the mean values of all observed and simulated samples.

5.4.1 Validation of instantaneous reaction delay models

The observed and simulated reaction delay by Ozaki and NN delay models are listed in Table 5.2. From the interval between 25% and 75% and the mean value, there are nearly no differences between the observed and simulated results. From the standard deviation, the correlation coefficient R and the mean square error E, however, the differences are significant. We note that the standard deviation in NN delay model is somewhat similar to the real value, but the value in Ozaki delay model is less than half of the real value. R in NN delay model is almost two times greater than that in Ozaki delay model, and E in NN delay model is less than half of that in Ozaki delay model. The results quantitatively show that NN delay model is more realistic than Ozaki delay model.

Table 5.2 Observed and simulated reaction delay by Ozaki and NN delay models.

	Percentile from 25% to 75%	Mean value	Standard deviation	R	E
Observed delay	[0.8, 1.1]	0.98	2.63	1	0
Ozaki delay	[0.9, 1.1]	0.98	1.23	0.43	5.62
NN delay	[0.8, 1.1]	0.98	2.06	0.77	2.78

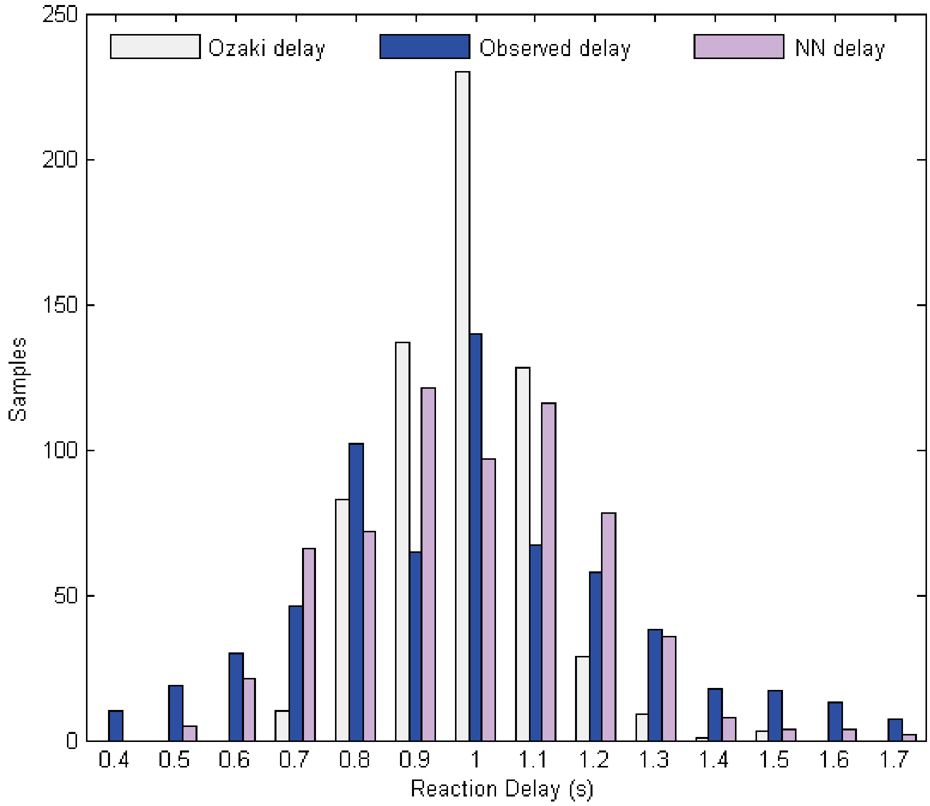

Fig. 5.5 Distribution of observed and simulated reaction delay.

Fig. 5.5 provides the distribution of observed and simulated reaction delay. It shows that observed values are more dispersed than simulated ones and the most of the values in Ozaki delay model distribute between 0.9 and 1.1 seconds. Obviously, the distribution in NN delay model is more consistent with the real distribution.

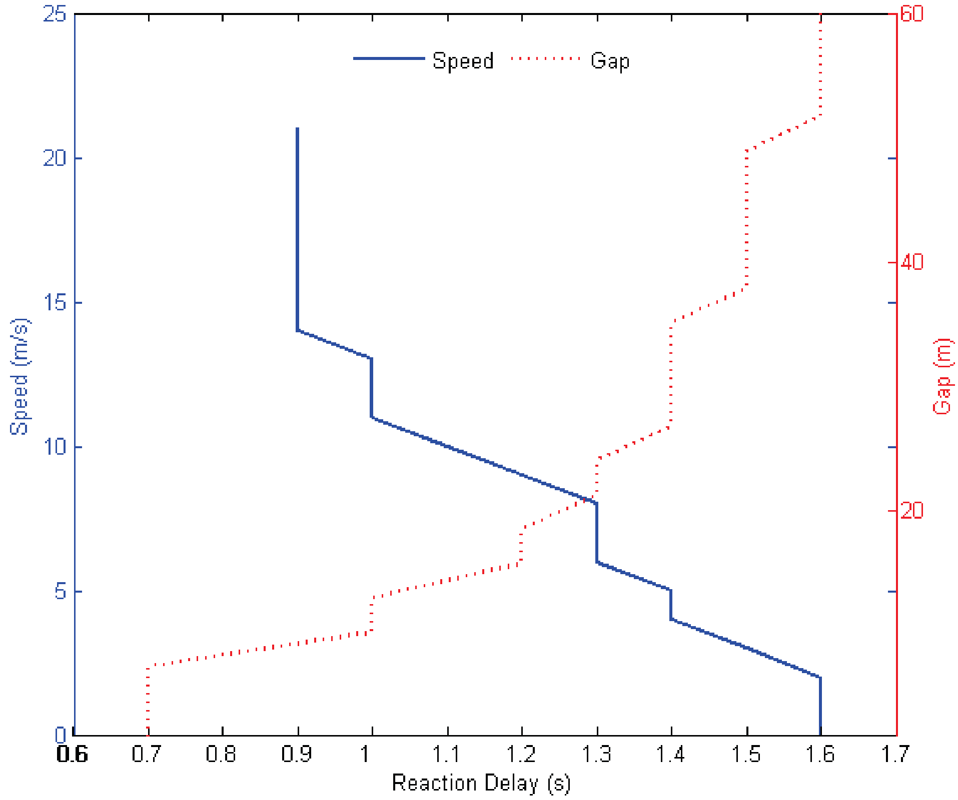

Fig. 5.6 Reaction delay at the different speed and gap in NN delay model.

Compared with statistical models in which the impact of each independent variable on the dependent variable can be clearly explained by the sign and magnitude of the corresponding parameter, the inherent explanatory power in neural networks is limited, which is known as the "black box" disadvantage. To find out the effect of the input of interest on the neural network output, sensitivity analysis is typically carried out.

In Fig. 5.6, reaction delay in NN delay model at the different speed and gap is displayed. We can see that, with the increase of speed reaction delay decreases, while with the increment of the gap reaction delay increases. To some extent, this is consistent with common driving experience. When the vehicle runs fast, the diver is usually more cautious and the time needed for the vehicle reaction is shorter too. When the gap is relatively large, without the collision risk the driver may not hurry to react to current traffic conditions.

5.4.2 Validation of car-following models

Nine cars that follow each other in the third lane are selected from the trajectory data set. Movements of the eight following vehicles are simulated by neural-network-based car-following models with different reaction delay. The first vehicle is fed into simulation. The observed and simulated speed and gaps are illustrated in Figs. 5.7 and 5.8.

By Fig. 5.7, we can see that, except the model with 1.5-second delay, the models are all able to accurately imitate the speed of the eight following vehicles. Particularly, the stop-and-go driving behavior is exactly modeled. Although observed speed profiles seem to be more coarse than simulated ones, it is believed that sharp fluctuations in observed speed profiles are largely caused by errors in deriving the speed from observed vehicle trajectories, since in reality for comfortable driving and fuel saving drivers seldom continually adjust their speed sharply. Moreover, it is also noted that the speed profiles in the model with 0.5-second delay are more compact than those in other models. This is largely due to the relatively short reaction delay with which following vehicles can react quickly to the change of traffic conditions. In the model with 1.5-second delay, following vehicles do not stop when the first vehicle stands still, that is, collisions occur in simulation. This mainly results from the quite long reaction delay of the driver-vehicle unit such that the speed cannot be adjusted in time.

In Fig. 5.8, on the whole, the simulated gaps are similar to the real gaps, apart from the model with 1.5-second delay. However, some differences can also be observed. During the first 30 seconds, in reality, vehicle 3 maintains relatively large gaps with vehicle 2, but the vehicles behind vehicle 3 maintain quite appropriate gaps. This may be due to that the following drivers act with the anticipation of their leading vehicles' next

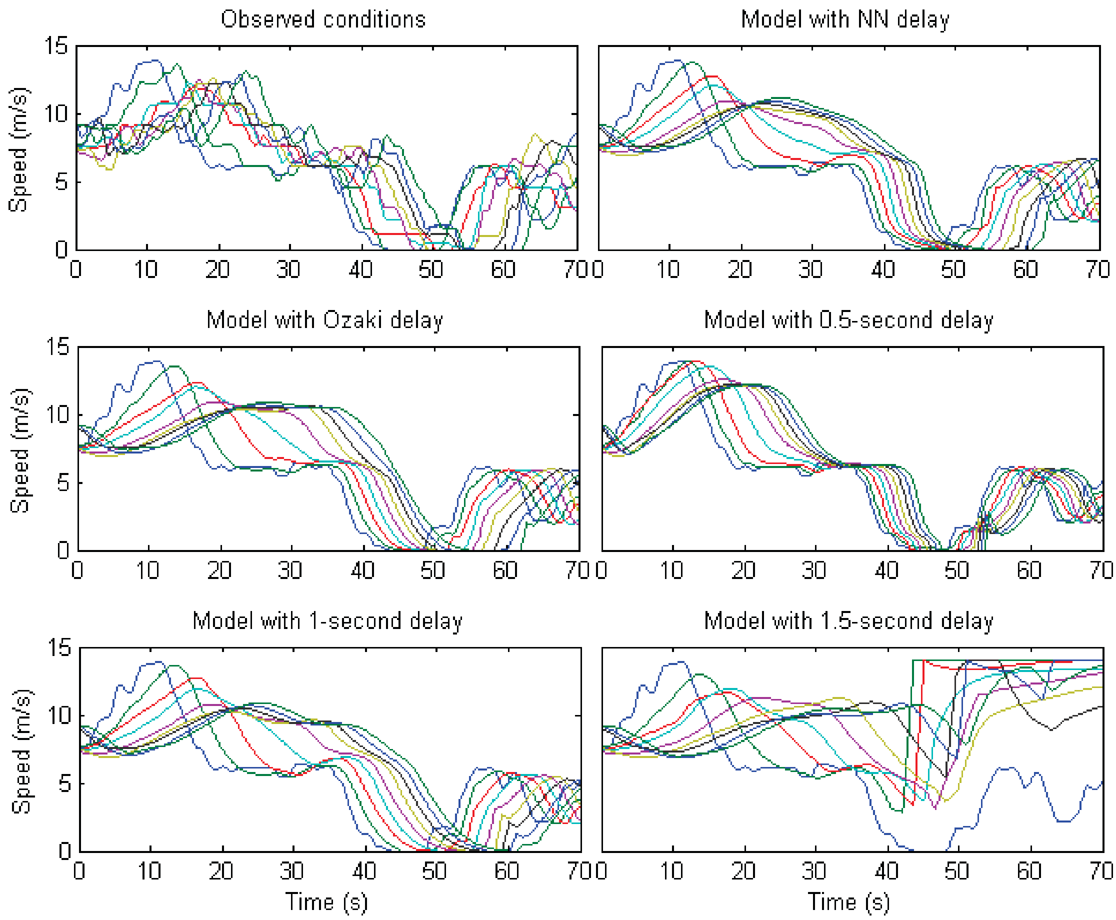

Fig. 5.7 Observed and simulated speed by models with different delay.

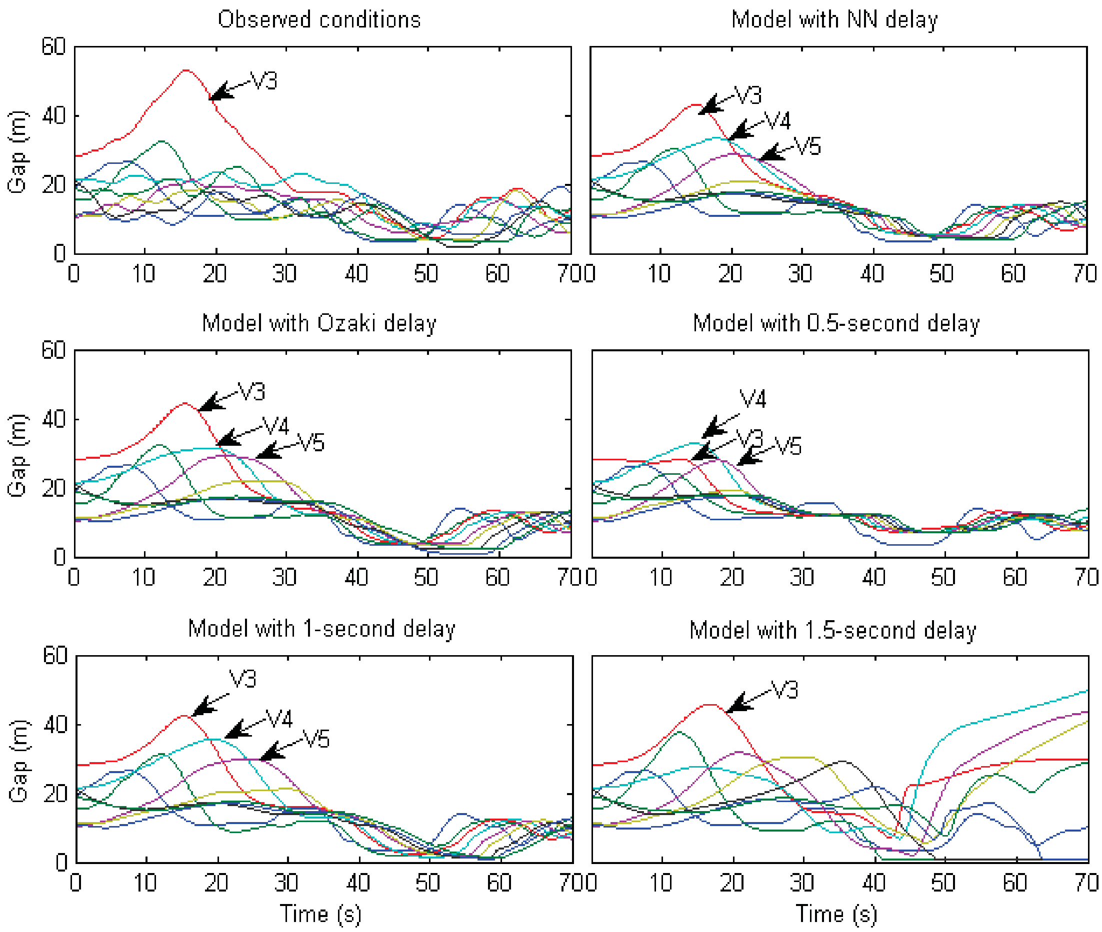

Fig. 5.8 Observed and simulated gaps by models with different delay.

actions. When vehicle 3 is going to accelerate to follow vehicle 2, vehicles behind vehicle 3 can estimate such intention and accelerate in time. In simulation, the relatively large gaps of vehicle 3 during the first 30 seconds are somewhat represented except in the model with 0.5-second delay, although the maximum value is less than the observed one. Besides, it is also noted that, the simulated vehicles 4 and 5 maintain greater gaps with their leading vehicles than observed vehicles do during the first 30 seconds. Although we adopt the gap of the leading vehicle as an input element in the car-following model to reflect the driver's anticipation ability, such ability is not well learned.

Possible reasons for the failure are that representative samples are not contained in the training data set, or drivers may estimate the movements of their leading vehicles depending not only on the gap but also on other traffic conditions such as the existence of vehicles in adjacent lanes.

Table 5.3 Statistical summary for each observed and simulated vehicles

Vehicle number			V2	V3	V4	V5	V6	V7	V8	V9	Mean value
Observed conditions	Mean speed		5.8	6.0	6.2	6.2	6.3	6.5	6.4	6.5	6.2
	Mean gap		12.5	23.3	17.0	13.2	12.0	11.4	11.6	13.3	14.3
Model with NN delay	Mean speed		5.7	6.0	6.2	6.2	6.3	6.4	6.4	6.5	6.2
	Mean gap		13.4	18.8	17.0	14.6	12.5	12.5	11.3	12.4	14.1
	R	Speed	0.99	0.97	0.97	0.97	0.92	0.93	0.89	0.89	0.94
		Gap	0.98	0.97	0.82	0.93	0.77	0.87	0.64	0.90	0.86
	E	Speed	0.29	0.70	0.73	0.82	1.98	1.85	2.83	3.00	1.53
		Gap	4.82	33.30	31.57	14.28	10.92	6.87	11.36	8.51	15.20
Model with Ozaki delay	Mean speed		5.7	6.0	6.2	6.2	6.3	6.4	6.4	6.5	6.2
	Mean gap		13.1	18.3	16.3	14.3	12.7	11.7	10.4	11.9	13.6
	R	Speed	0.99	0.98	0.98	0.95	0.89	0.90	0.86	0.86	0.93
		Gap	0.98	0.98	0.82	0.90	0.67	0.85	0.59	0.87	0.83
	E	Speed	0.25	0.48	0.72	1.22	2.59	2.52	3.70	3.98	1.93
		Gap	2.74	33.8	34.2	20.53	19.54	8.16	20.55	11.36	18.86
Model with 0.5-second delay	Mean speed		5.7	6.0	6.1	6.2	6.2	6.4	6.4	6.5	6.2
	Mean gap		12.9	14.9	15.7	13.9	12.1	13.0	11.9	13.0	13.4
	R	Speed	0.98	0.91	0.93	0.93	0.88	0.84	0.81	0.79	0.88
		Gap	0.96	0.78	0.71	0.86	0.79	0.70	0.37	0.88	0.76
	E	Speed	0.52	2.76	2.20	2.01	3.21	4.19	4.87	5.70	3.18
		Gap	12.60	154.10	35.51	9.72	6.86	13.69	14.74	11.28	32.31
Model with 1-second delay	Mean speed		5.7	6.0	6.2	6.3	6.3	6.5	6.5	6.6	6.3
	Mean gap		12.2	17.7	16.6	14.5	12.4	11.4	10.6	11.7	13.4
	R	Speed	0.99	0.97	0.98	0.95	0.90	0.90	0.86	0.87	0.93
		Gap	0.97	0.97	0.83	0.87	0.70	0.88	0.65	0.88	0.84
	E	Speed	0.33	0.81	0.52	1.11	2.31	2.25	3.27	3.28	1.73
		Gap	3.82	42.69	50.59	29.24	19.36	6.63	15.21	11.17	22.34

Table 5.3 provides the statistical summary of each observed and simulated vehicles. It is shown that, compared with other vehicles, for vehicle 2 the models all acquire their best performance, which indicates that validating the models by using the data only from one vehicle in previous studies (Khodayari et al. 2012; Panwai and Dia 2007) is insufficient. Furthermore, among all the models, the model with Ozaki delay achieves the highest accuracy for vehicle 2, but for vehicles 3 through 9 together with the mean value, the model with NN delay apparently outperforms other models. The results also quantitatively illustrate that the models with instantaneous reaction delay simulate the movements of vehicles more realistically than the models with fixed reaction delay do, which is in agreement with the conclusion in (Khodayari et al. 2012).

5.5 Conclusions

Reaction delay of the driver-vehicle unit varies greatly according to driver-vehicle characteristics and traffic conditions, and is an indispensable factor for modeling vehicle movements. However, estimation of these variations is almost impossible in classic paradigms so that fixed reaction delay was adopted in previous studies. Based on the time delay between the relative gap and acceleration, Khodayari et al. (2012) defined the reaction delay of driver-vehicle unit and modeled the movements of the vehicle used for reaction delay estimation. In this study, some limitations in (Khodayari et al. 2012) are pointed out. And, by redefining driver-vehicle reaction delay, a neural network for instantaneous reaction delay is trained using samples observed from real traffic.

Incorporating the reaction delay network into a neural-network-based car-following model, movements of nine vehicles which follow each other are simulated.

Simulation results show that, for all discussed models, vehicle 2 is simulated with the highest accuracy, since the first vehicle is fed into simulation. This indicates that in previous studies validating the models by using the data only from one vehicle is insufficient. Moreover, we find that the performance of the models with instantaneous reaction delay is apparently better than that of the models with fixed delay. In the model with short fixed reaction delay, the simulated vehicles follow each other more closely than the observed vehicles do, and collisions occur in the model with long fixed delay, which also illustrates the necessity of taking into account instantaneous reaction delay in vehicle movement modeling. Besides, for future reference, the calibrated weights and bias in the neural-network-based reaction delay and car-following models are presented in Appendix.

Finally, we point out that due to lack of available data, in this study the proposed methodology was not validated in some different contexts, such as in a rainy day. Typically, in different contexts the accuracy of the models will be reduced to some extent, if we still use the same parameters. In actual practice, we usually recalibrate the models by using the data collected in the corresponding context and adopt different W^1, b^1, W^2, b^2 in the Appendix. In addition, although more and more car-following and lane-changing models that can take a wide variety of driver-vehicle characteristics into consideration have been proposed so far, car-following and lane-changing behavior are usually treated individually. This is obviously inconsistent with the real driving behavior. A model framework that can integrate the acceleration and lane-changing behavior was developed in (Toledo et al. 2007), but some driver-vehicle characteristics were avoided, such as instantaneous reaction delay and lane-changing duration. By using the neural network technology, an integrated methodology for the vehicle two-dimensional movements (longitudinal and lateral) comprises our further study.

Appendix

The calibrated weights and bias in the neural network for instantaneous reaction delay:

$$W^1 = \begin{pmatrix} -0.03 & 2.79 & -1.96 & 3.62 \\ 19.77 & -16.68 & -17.03 & -23.61 \\ 0.10 & 0.66 & 0.37 & -0.04 \\ -10.00 & 2.63 & -1.31 & -0.25 \\ 2.33 & -2.49 & 0.05 & -2.19 \\ -0.15 & -0.68 & 1.10 & 1.80 \\ 0.51 & 0.07 & -0.62 & -0.09 \\ -8.01 & 11.08 & -5.88 & 9.08 \\ 1.84 & -5.87 & 4.45 & 0.33 \\ -0.07 & -0.73 & -0.36 & 0.02 \end{pmatrix} \quad \mathrm{b}^1 = \begin{pmatrix} 0.27 \\ -9.69 \\ 0.03 \\ -2.29 \\ 10.49 \\ -15.80 \\ 0.38 \\ 11.16 \\ -13.67 \\ 0.30 \end{pmatrix} \quad W^2 = \begin{pmatrix} 2.48 \\ -0.18 \\ -2.70 \\ 3.12 \\ -0.17 \\ 0.27 \\ -1.01 \\ -0.22 \\ 0.05 \\ -2.77 \end{pmatrix} \quad \mathrm{b}^2 = 1.62$$

The calibrated weights and bias in the car-following neural network:

$$W^1 = \begin{pmatrix} 22.76 & 7.78 & -9.17 & -2.33 \\ -1.98 & 2.93 & 3.01 & 1.81 \\ -0.27 & 0.34 & 0.20 & 0.14 \\ -2.44 & 0.89 & -4.66 & -0.62 \\ -2.09 & -3.81 & 2.01 & 1.31 \\ 1.01 & 0.02 & -1.20 & 2.81 \\ -18.16 & -8.02 & -3.82 & 6.53 \\ -0.92 & 0.56 & -0.02 & 0.32 \\ -0.06 & -0.02 & 0.01 & 0.01 \\ -2.82 & 8.91 & -19.20 & 14.77 \end{pmatrix} \quad \mathrm{b}^1 = \begin{pmatrix} -2.21 \\ -0.94 \\ -2.57 \\ 3.14 \\ 1.58 \\ -18.35 \\ -10.80 \\ -2.56 \\ 0.45 \\ -1.23 \end{pmatrix} \quad W^2 = \begin{pmatrix} -0.01 \\ -0.85 \\ 0.03 \\ -2.90 \\ -0.95 \\ 0.01 \\ -0.04 \\ 0.06 \\ -1.17 \\ -0.01 \end{pmatrix} \quad \mathrm{b}^2 = -0.54$$

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CHAPTER 6. PREDICTING DRIVER'S LANE-CHANGING DECISIONS USING A NEURAL NETWORK MODEL

6.1 Introduction

Owing to the ability to capture the complexity of traffic systems, traffic simulation has become one of the most widely used approaches for traffic planning, traffic design, and traffic management. Various traffic simulation software packages are currently available in the market, and they are utilized by thousands of consultants, researchers, and public agencies (Barceló, J. 2010; Bloomberg, L. and Dale, J 2000; Hidas, P. 2005; Kondyli, A. et al. 2012). With the popularity of traffic simulation, the car-following and lane-changing models, two of the most significant components in traffic simulation, have naturally attracted a lot of attention from traffic researchers (Brackstone and McDonald 1999; Toledo 2007; Zheng et al. 2012a; Zheng et al. 2012b).

According to previous studies, lane changing has a significant impact on traffic flow characteristics owing to the inference effect on surrounding vehicles (Daganzo et al. 1999). In addition, lane changing is also viewed as a key trigger in freeway breakdown (Duret et al. 2011; Jiang and Adeli 2004), and it potentially reduces freeway safety (Jin 2010; Mauch and Cassidy 2002). To describe such driving behavior more accurately, over the past two decades, several lane-changing models have been developed

(Gipps1986; Hidas 2002; Laval and Daganzo 2006; Sheu and Ritchie 2001; Sun and Kondyli 2010; Toledo et al. 2003; Aghabayk et al. 2011).

However, compared to the car-following model, literature relating to lane changing is less comprehensive. This may be owing to two reasons: the inherent complexity of lane changing and the absence of large-scale data to analyze such behavior. Unlike car following, lane changing is influenced not only by preceding and following vehicles in the same lane but also by leading and lagging vehicles in adjacent lanes (Moridpour et al. 2010). Besides, driver's decisions to change lane are also affected by driver characteristics (age, gender, driving experience) and driving attitudes (aggressive or conservative driver) (Sun and Elefteriadou 2010; Sun and Elefteriadou 2012). As a result, the prediction of driver's lane-changing decisions is extremely complicated. On the other hand, models should be estimated and validated by field data (Hollander and Liu 2008). However, most of the previous lane-changing models were proposed without rigorous estimation and validation, largely owing to a lack of available data (Gipps1986; Hidas 2002; Sheu and Ritchie 2001).

In an effort to cope with the obstacles affecting the modeling of lane changing, in this study, a neural network (NN) model is adopted to capture the inherent complexity of lane changing, and large-scale trajectory data are used for model estimation and validation. Specifically, this study makes the following contributions. (1) A detailed analysis of left and right lane changes is conducted, which suggests that the left and right lane changes are asymmetric and incentivized by different motivations. (2) A NN model that can completely account for the impact of surrounding vehicles on lane-changing decisions is developed. In addition, the proposed NN model clearly outperforms a multinomial logit (MNL) model, which was frequently adopted as a framework for lane changing in previous studies, both in model estimation and validation processes. (3) The impact of heavy vehicles on driver's lane-changing decisions is quantitatively evaluated using the sensitivity analysis of the proposed NN model.

The paper is composed of eight sections. Sec. 6.2 discusses the specification of our model, and is followed by the introduction and analysis of trajectory data in Sec. 6.3. Model estimation and validation are presented in Secs. 6.4 and 6.5, respectively. The application of the proposed model is demonstrated in Sec. 6.6. Secs. 6.7 and 6.8 are devoted to further discussions and conclusions.

6.2 Model Specification

Depending on the purpose, lane changing is categorized as being either mandatory or discretionary (Gipps1986). Typically, mandatory lane changing is executed when the driver must leave the current lane to maintain the desired route. Discretionary lane changing refers to cases in which the driver changes lane to improve driving conditions, such as overtaking slow vehicles, passing large/heavy vehicles, and avoiding traffic near an on-ramp. In addition, lane-changing maneuvers are different for different types of vehicles (heavy vehicle or car) (Aghabayk et al. 2011; Moridpour et al. 2010). In this study, we only discuss the discretionary lane changing of cars. In fact, the proposed methodology can also be applied to heavy vehicles or mandatory lane-changing vehicles by defining them as subject vehicles.

The subject vehicle and its surrounding vehicles are illustrated in Fig. 6.1. Note

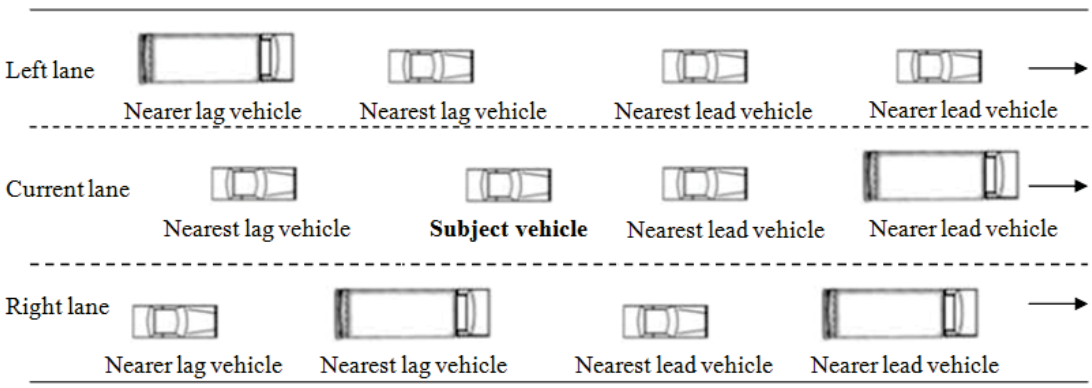

Fig. 6.1 Illustration of the subject vehicle and its surrounding vehicles.

that in this study, not only are the nearest lead and lag vehicles in the current and adjacent lanes considered but also the nearer lead and lag vehicles. To facilitate model specification, the following variables are employed:

L_{id} = ID of the current lane for the subject vehicle;

V = instantaneous speed of the subject vehicle;

$T_{lead}^{nearest}$ = type of the nearest lead vehicle;

$RV_{lead}^{nearest}$ = relative speed between the nearest lead vehicle and subject vehicle;

$SG_{lead}^{nearest}$ = space gap between the nearest lead vehicle and subject vehicle;

T_{lead}^{nearer} = type of the nearer lead vehicle;

RV_{lead}^{nearer} = relative speed between the nearer and nearest lead vehicles;

SG_{lead}^{nearer} = space gap between the nearer and nearest lead vehicles.

Accordingly, $T_{lag}^{nearest}, RV_{lag}^{nearest}, SG_{lag}^{nearest}, T_{lag}^{nearer}, RV_{lag}^{nearer}, SG_{lag}^{nearer}$ are variables with respect to the subject vehicle, the nearest, and nearer lag vehicles.

6.2.1 Neural network model

Since the 1990s, there has been an increased interest in a wide variety of disciplines concerning the application of artificial NNs (Adeli 2001; Kalyoncuoglu and Tigdemir 2004; Hunt and Lyons 1994; Kalogirou 2000; Karlaftis and Vlahogianni 2011; Rafiq et al. 2001; Hagan et al. 1996). Typically, two advantages contribute to the popularity of NN models. One of them is that NNs are able to handle noisy data and approximate any degree of complexity in nonlinear systems (Adeli 2001; Hunt and Lyons 1994; Rafiq et al. 2001). Another advantage is that NN models do not require any simplifying assumptions or prior knowledge of problem solving, compared with statistical models (Kalyoncuoglu and Tigdemir 2004; Karlaftis and Vlahogianni 2011). For example, in regression models, we have to specify the underlying relationship (linear, polynomial, exponential, rational, etc.) between independent and dependent variables before model estimation. However, such specifications are not necessary for inputs and outputs in NN models.

In (Hunt and Lyons 1994), Hunt and Lyons used two sorts of NNs to model a driver's lane-changing behavior. In the prediction-type network, drivers are unable to change lanes because the model is trained by the simulated data from an individual subject driver, where the portion of lane-change instances is very small. The application of a classification-type NN is considered to be viable. The model is able to correctly classify a very high proportion of examples during training for both simulated and observed data. However, it is also noted that misclassification of unseen driving examples is highly significant in the testing process. Besides, only the effect of the position of surrounding vehicles on the subject vehicle's lane changing is considered in the classification-type network. The relative speed and the vehicle type of surrounding vehicles, which also greatly influences lane changing (Moridpour et al. 2010), are not considered.

The NN considered in this study is a typical feed-forward NN with five layers (an input layer, three hidden layers, and an output layer), as displayed in Figure 2. If we relate the model to a biological neuron, the weights and bias (IW, LW, b_i) correspond to the strength of a synapse, a cell body is represented by the summation and transfer functions (f(x), g(x)), and the output (OP) represents the signal on an axon (Hagan et al. 1996). Training is the process of modifying the weights and bias using a suitable learning method. The network uses a learning mode, in which the inputs and desired outputs are presented to the network and the weights and bias are adjusted so that the network attempts to produce the desired outputs. After training, the weights and bias contain meaningful information, whereas before training, they are random and have no meaning (Kalogirou 2000).

In the input layer of the proposed model, there are three input vectors, each of which separately connects a hidden layer. Elements in each input vector are the variables associated with the vehicles in the left (L), current (C), and right (R) lanes, respectively.

$$\begin{aligned} IP^L \text{ or } IP^R = \{&T_{lead}^{nearest}, T_{lead}^{nearer}, RV_{lead}^{nearest}, RV_{lead}^{nearer}, SG_{lead}^{nearest}, SG_{lead}^{nearer}, \\ &T_{lag}^{nearest}, T_{lag}^{nearer}, RV_{lag}^{nearest}, RV_{lag}^{nearer}, SG_{lag}^{nearest}, SG_{lag}^{nearer}\}, \end{aligned} \tag{6.1}$$

$$\begin{aligned} IP^C = \{&L_{id}, V, T_{lead}^{nearest}, T_{lead}^{nearer}, RV_{lead}^{nearest}, RV_{lead}^{nearer}, \\ &SD_{lead}^{nearest}, SD_{lead}^{nearer}, T_{lag}^{nearest}, RV_{lag}^{nearest}, SD_{lag}^{nearest}\}. \end{aligned} \tag{6.2}$$

The transfer function in the hidden layers is a hyperbolic tangent sigmoid function

$$f_i(x) = \frac{2}{1+\exp(-2x)} - 1,\ i \in [L, C, R] \tag{6.3}$$

This function is inherently nonlinear and produces outputs with upper and lower bounds, which is considered suitable for complicated systems. The number of neurons in each hidden layer will be determined by model estimation in the next section. According to lane-changing directions, three neurons are employed in the output layer. The transfer function adopted in the output layer is defined as follows:

$$g(x_i) = \frac{\exp(x_i)}{\sum_{j\in[L,C,R]} \exp(x_j)},\ i \in [L, C, R] \tag{6.4}$$

Such a design provides the exact probability of making each decision, unlike the pattern recognition network, where outputs are represented by zeros or ones. Furthermore, it facilitates the comparison with an MNL model that will be discussed later. The Levenberg–Marquardt back-propagation algorithm (Hagan et al. 1996) is used for

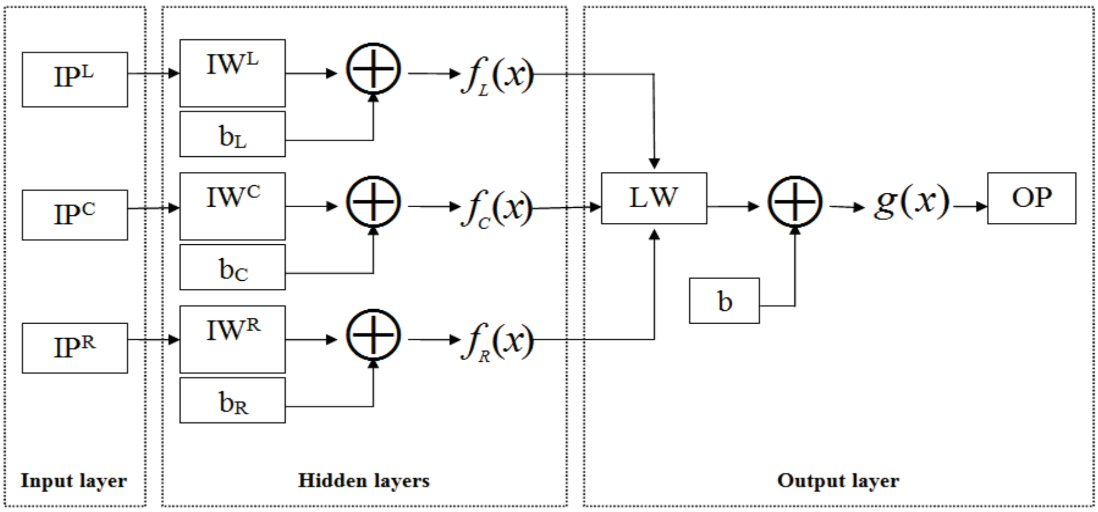

Fig. 6.2 The NN used for lane-changing decisions

training owing to its fast speed. The mean square error (MSE) is taken as a measure of the performance of the NN model, and is given by

$$MSE = \frac{1}{N}\sum\nolimits_{i \in [L,C,R]} (OB_i - OP_i)^2, \tag{6.5}$$

where OB and OP are the observed lane-changing decisions and the predicted probability, respectively. N is the number of total samples.

6.2.2 Multinomial logit model

In previous studies, the discrete choice model was often adopted as a framework for lane changing (Toledo et al. 2003; Sun and Elefteriadou 2010). For comparison purposes, an MNL model of lane-changing decisions was also developed in this study.

In accordance with discrete choice theory (Ben-Akiva and Lerman 1985), the total utility of choosing an alternative is composed of two components, the observed utility V_i and the unobserved error term ε_i,

$$U_i = V_i + \varepsilon_i,\ i \in [L,C,R]. \tag{6.6}$$

Based on driving conditions, the observed utility for each lane is defined as

$$\begin{aligned} V_L = C_1 &+ \beta_3 T_{lead}^{nearest} + \beta_4 RV_{lead}^{nearest} + \beta_5 SG_{lead}^{nearest} + \beta_6 T_{lead}^{nearer} + \beta_7 RV_{lead}^{nearer} + \beta_8 SG_{lead}^{nearer} \\ &+ \beta_9 T_{lag}^{nearest} + \beta_{10} RV_{lag}^{nearest} + \beta_{11} SG_{lag}^{nearest} + \beta_{12} T_{lag}^{nearer} + \beta_{13} RV_{lag}^{nearer} + \beta_{14} SG_{lag}^{nearer}, \end{aligned} \tag{6.7}$$

$$\begin{aligned} V_C = C_2 &+ \beta_1 L_{id} + \beta_2 V + \beta_3 T_{lead}^{nearest} + \beta_4 RV_{lead}^{nearest} + \beta_5 SG_{lead}^{nearest} + \beta_6 T_{lead}^{nearer} + \beta_7 RV_{lead}^{nearer} \\ &+ \beta_8 SG_{lead}^{nearer} + \beta_9 T_{lag}^{nearest} + \beta_{10} RV_{lag}^{nearest} + \beta_{11} SG_{lag}^{nearest}, \end{aligned} \tag{6.8}$$

$$\begin{aligned} V_R = C_3 &+ \beta_3 T_{lead}^{nearest} + \beta_4 RV_{lead}^{nearest} + \beta_5 SG_{lead}^{nearest} + \beta_6 T_{lead}^{nearer} + \beta_7 RV_{lead}^{nearer} + \beta_8 SG_{lead}^{nearer} \\ &+ \beta_9 T_{lag}^{nearest} + \beta_{10} RV_{lag}^{nearest} + \beta_{11} SG_{lag}^{nearest} + \beta_{12} T_{lag}^{nearer} + \beta_{13} RV_{lag}^{nearer} + \beta_{14} SG_{lag}^{nearer}, \end{aligned} \tag{6.9}$$

where C_1, C_2, C_3 are alternative-specific constants and βs (s = 1, 2, 3, …,14) are corresponding parameters to be estimated.

Assuming that the unobserved error terms ε_i, $i \in [L, C, R]$ are independent and identically Gumbel-distributed across alternatives and choice occasions, the probability of changing into adjacent lanes or keeping the current lane in the next time step can be calculated as

$$P_i = \frac{\exp(V_i)}{\sum_{j \in [L,C,R]} \exp(V_j)},\ i \in [L, C, R]. \tag{6.10}$$

6.3 Data Sets

The data used in this study were collected on a segment of U.S. Highway 101 in Los Angeles, California, where an on-ramp and off-ramp were covered using several video cameras mounted on a multistory building. The datasets were provided by Cambridge Systematic Incorporation for Federal Highway Administration as a part of the Next Generation Simulation (NGSIM) program. Detailed information about observed vehicles (vehicle type and size, lane ID, two-dimension position, speed, and acceleration) was extracted from the video data, along with information about the preceding and following vehicles. Traffic is composed of three different vehicle classes, namely motorcycle, automobile, and truck.

Data reflecting congested traffic conditions in morning peak periods were collected between 7:50 am and 8:20 am on June 15, 2005. Because only the discretionary lane changing is discussed in this study, mandatory lane-changing vehicles entering the freeway from the on-ramp or exiting to the off-ramp are excluded from the trajectory data. Data collected from 7:50 am to 8:05 am and 8:05 am to 8:20 am, which are hereafter denoted as dataset 1 and dataset 2, are used for model estimation and validation, respectively. A detailed analysis of the data and the data processing methodology is presented in the NGSIM U.S. 101 Data Analysis Report (Cambridge Systematics Inc. 2005). In addition, to alleviate the noise in the data (Punzo et al. 2011), the moving-average filter for the duration of one second is applied to all vehicle trajectories.

In this study, a lane change is assumed to be instantaneous without duration. The instance at which a vehicle crosses over the current lane line in the next time step is treated as a lane-changing instance. Therefore, lane-changing instances are greatly outnumbered by car-following or free-flow instances during a driver's journey. It is impossible to train the NN model using continuous trajectories of lane-changing vehicles. This is also the reason for the failure of the prediction-type network in (Hunt and Lyons 1994). To mitigate this issue, in this study, samples were drawn from trajectory data. For a lane-changing vehicle, lane-changing instances were selected and two additional non-lane-changing instances were chosen randomly. For a non-lane-changing vehicle, three samples were randomly drawn. A total of 5826 samples were drawn from dataset 1, which consists of 332 left-changing samples, 5284 non-lane-changing samples, and 210 right lane-changing samples. The number of left lane-changing, non-lane-changing, and right lane-changing samples from dataset 2 were 223, 5030, and 112, respectively.

To obtain a clear view on the causes of lane changes, the summary statistics of left and right lane-changing samples are presented in Tables 6.1 and 6.2, respectively. The Kolmogorov–Smirnov (KS) test is applied to compare the distribution of the variables in two different lanes, where the result is one if the distribution is different at the 5% significance level, and otherwise zero.

For left lane-changing samples in Table 6.1, the mean relative speed and mean space gap with the nearest lead vehicle in the left lane are obviously superior to that in the current and right lanes. Although the mean space gap between the nearest and nearer lead vehicles in the left lane is also greater than that in other lanes, the KS test does not show differences in their distribution. The results in the mean relative speed between the subject vehicle and the nearest lag vehicle are similar to that in the mean space gap between the nearest and nearer lead vehicles. From Table 6.2, both the mean relative

Table 6.1 Summary statistics for 555 left lane-changing samples

Variables	Corresponding lane	Percentile from 25% to 75%	Mean	Standard deviation	KS test
	Left lane	[-0.8, 1.3]	0.4	2.5	Left-Current lane = 1
$RV_{lead}^{nearest}$ (m/s)	Current lane	[-2.3, 0.3]	-0.8	2.7	Current-Right lane = 1
	Right lane	[-2.2, 1.0]	-0.5	3.0	Right-Left lane = 1
	Left lane	[8.0, 24.8]	18.3	13.4	Left-Current lane = 1
$SG_{lead}^{nearest}$ (m)	Current lane	[8.0, 17.8]	14.2	9.9	Current-Right lane = 1
	Right lane	[1.3, 18.7]	11.0	13.0	Right-Left lane = 1
	Left lane	[-0.8,1.2]	0.2	1.7	Left-Current lane = 1
RV_{lead}^{nearer} (m/s)	Current lane	[-0.2, 1.5]	0.6	1.9	Current-Right lane = 0
	Right lane	[-0.5, 1.4]	0.6	2.3	Right-Left lane = 1
	Left lane	[13.7, 30.7]	23.3	11.7	Left-Current lane = 0
SG_{lead}^{nearer} (m)	Current lane	[13.4, 28.5]	22.1	12.2	Current-Right lane = 0
	Right lane	[13.3, 27.9]	21.8	11.5	Right-Left lane = 0
	Left lane	[-0.3, 2.2]	1.3	2.6	Left-Current lane = 0
$RV_{lag}^{nearest}$ (m/s)	Current lane	[-0.4, 2.1]	0.9	2.4	Current-Right lane = 0
	Right lane	[-0.6, 2.5]	0.9	2.7	Right-Left lane = 0
	Left lane	[12.3, 27.4]	21.1	12.3	Left-Current lane = 1
$SG_{lag}^{nearest}$ (m)	Current lane	[13.4, 33.1]	24.1	14.2	Current-Right lane = 1
	Right lane	[3.1, 21.8]	14.4	14.3	Right-Left lane = 1

Table 6.2 Summary statistics for 322 right lane-changing samples

Variables	Corresponding lane	Percentile from 25% to 75%	Mean	Standard deviation	KS test
	Left lane	[-1.9, 0.2]	-0.8	2.2	Left-Current lane = 0
$RV_{lead}^{nearest}$ (m/s)	Current lane	[-1.5, 0.5]	-0.6	1.8	Current-Right lane = 1
	Right lane	[-0.7, 2.0]	0.7	2.2	Right-Left lane = 1
	Left lane	[-0.9, 13.2]	8.3	11.8	Left-Current lane = 1
$SG_{lead}^{nearest}$ (m)	Current lane	[9.8, 23.5]	18.1	10.6	Current-Right lane = 1
	Right lane	[6.3, 22.4]	16.2	13.2	Right-Left lane = 1
	Left lane	[-0.6, 1.1]	0.3	1.4	Left-Current lane = 0
RV_{lead}^{nearer} (m/s)	Current lane	[-0.5, 1.3]	0.4	1.7	Current-Right lane = 0
	Right lane	[-0.9, 1.0]	0.2	1.6	Right-Left lane = 0
	Left lane	[13.3, 24.1]	21.0	11.2	Left-Current lane = 0
SG_{lead}^{nearer} (m)	Current lane	[12.9, 24.0]	19.1	10.2	Current-Right lane = 0
	Right lane	[14.0, 29.6]	23.1	12.3	Right-Left lane = 0
	Left lane	[-1.0, 2.2]	0.7	2.2	Left-Current lane = 1
$RV_{lag}^{nearest}$ (m/s)	Current lane	[-0.4, 1.6]	0.8	2.2	Current-Right lane = 1
	Right lane	[-1.3, 1.4]	0.3	2.7	Right-Left lane = 0
	Left lane	[3.0, 19.0]	13.2	14.1	Left-Current lane = 1
$SG_{lag}^{nearest}$ (m)	Current lane	[14.3, 32.9]	24.4	12.8	Current-Right lane = 1
	Right lane	[9.2, 29.2]	19.8	14.3	Right-Left lane = 1

speed between the nearest lead vehicle in the right lane and the subject vehicle and the mean space gap between the nearest and the nearer vehicles in the right lane are superior to that in the current and left lanes. However, from the KS test, the distribution of the space gap between the nearest and the nearer vehicles is not significantly different.

By comparing Tables 6.1 and 6.2, for left lane-changing samples, traffic conditions in the left lane are obviously better than those in the current and right lanes, while for right lane-changing samples, the superiority of the right lane is not very significant. This implies that left and right lane-changing decisions are incentivized by different motivations. The motivation for left lane changes may be to realize better driving conditions, but for right lane changes, it may be to allow a following vehicle to pass by. As a result, left and right lane changing are considered to be asymmetric and should be treated individually if the rule-based lane-changing model is proposed. However, this was not discussed in previous studies (Gipps1986; Hidas 2002; Toledo et al. 2003;Sun and Elefteriadou 2010). On the other hand, NN models appear to be capable of accounting for such asymmetry because the models have the ability to deal with complicated nonlinear systems and do not require any predefined underlying relationship between inputs and outputs (Kalyoncuoglu and Tigdemir 2004; Karlaftis and Vlahogianni 2011).

6.4 Model Estimation

In general, as the number of neurons used in the hidden layer increases, the accuracy of the NN model also increases in the model estimation process. However, the cost spent during model estimation and the over-fitting concern are also increased with the increase in the number of neurons (Yin et al. 2003). To make a better trade-off, the performance of the NN models with different number of neurons is checked by the MSE, as exhibited in Figure 3. In this study, the neural network is built by using the Neural Network Toolbox and implemented in MATLAB. In the learning process, 70% input samples are used for training and 30 % input samples for model validation. The maximum number of training iterations and the minimum performance gradient are set to 1000 and 1.0×10^{-5}, respectively. The result in Figure 3 is the minimum value of MSE in 10 simulation runs.

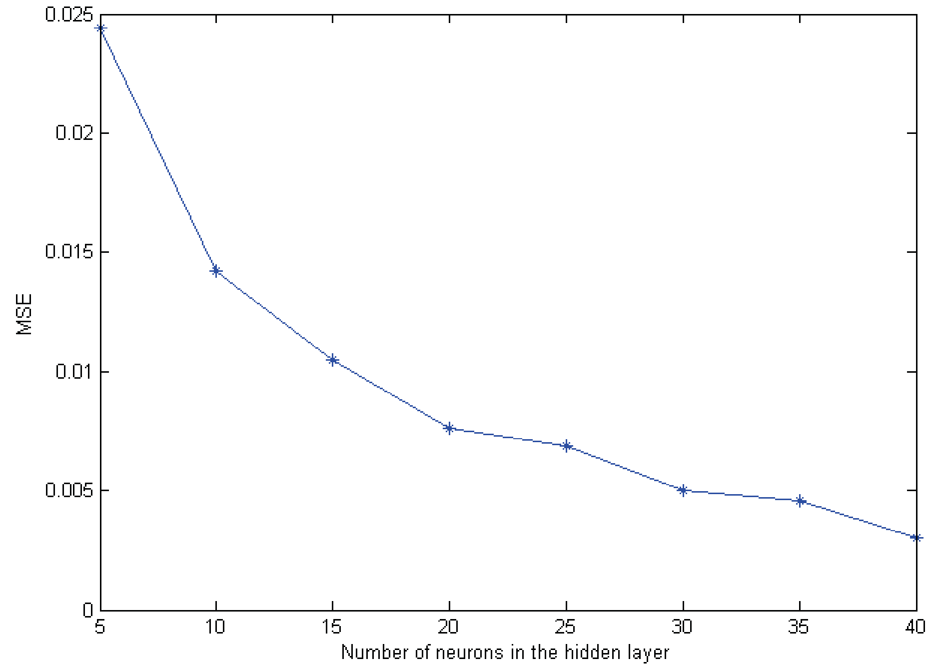

Fig. 6.3 MSE of the NN models with different number of neurons in a hidden layer

Table 6.3 Estimation results of the MNL model

Parameters	C_1	C_2	C_3	β_1	β_2	β_3	β_4	β_5	β_6
Value	-1.38	3.33	-1.94	-0.031	-0.217	0.079	0.257	0.045	0.02
T-test	0	0	0	-0.7	-14.71	0.87	9.53	14.55	0.22
Parameters	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}	β_{14}	
Value	0.087	-0.003	-0.142	0.047	0.03	-0.236	-0.042	0.001	
T-test	3.05	-0.91	-1.19	2.24	10.65	-2.3	-1.37	0.31	

Number of observations: 5826

Init log-likelihood: -5549.562 Final log-likelihood: -1647.593

Likelihood ration test: 7803.938 Rho-square: 0.703

Based on Figure 3, 20 neurons are employed in each hidden layer of the proposed model because the decreasing trend of the MSE is not significant when more than 20 neurons are used.

The MNL model is estimated by a free software package, Biogeme [36], and the results are listed in Table 3. From the Rho-square value, the MNL model achieves a desirable goodness of fit and the T-test explicitly reflects the significance of each variable. This also contrasts sharply with the "black box" disadvantage of the NN model, where the inherent explanatory power is limited.

6.5 Model Validation

In this section, the NN and MNL models are validated by two datasets: dataset 1, which was used for model estimation in the previous section, and dataset 2, which is new for the two models and includes 223 left lane-changing samples, 5030 non-lane-changing samples, and 112 right lane-changing samples.

To demonstrate the accuracy of the two models, we apply the estimated models to predict the probability of conducting the left/right lane change or maintaining the current lane in the next time step. For each sample, there are three predicted values that show the probability of executing left/right/non-lane changing based on the NN and MNL models. The distribution of the predicted probability for actual decisions in datasets 1 and 2 is illustrated in Figs 6.4 and 6.5, respectively, and the percentage of correct predictions is listed in Tables 6.4 and 6.5, respectively. Here, for an actual decision, if the predicted probability by the NN and MNL models is more than P (33.3% or 50% in Tables 6.4 and 6.5, respectively), the prediction is considered to be correct.

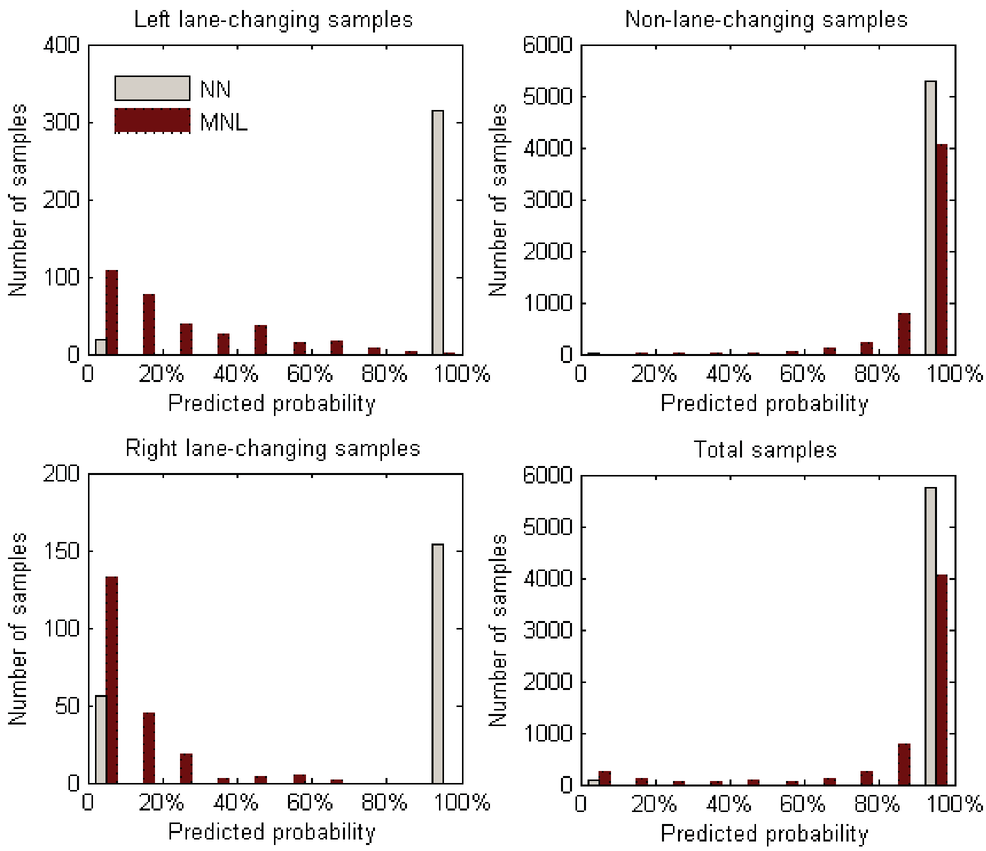

Fig. 6. 4 Distribution of predicted probability for actual decisions in dataset 1

Table 6.4 Percentage of correct predictions in dataset 1

	Left lane-changing samples		Non-lane-changing samples		Right lane-changing samples		Total samples	
Number of samples	332		5284		221		5826	
	NN	MNL	NN	MNL	NN	MNL	NN	MNL
P > 33.3%	94.58%	30.12%	99.86%	99.77%	73.33%	5.71%	98.63%	92.41%
P > 50%	94.58%	13.25%	99.86%	99.09%	73.33%	3.33%	98.63%	90.75%
KS test	1		1		1		1	

From the prediction results in dataset 1, for non-lane-changing samples, both the NN and MNL models can correctly forecast more than 99% of samples. However, for left lane-changing samples, the percentage correctly predicted in the NN model is greater than 94%, while that predicted in the MNL is less than 14%. Unsurprisingly, as implied by the data analysis in Section 3, the prediction of right lane changes is more difficult. For right lane-changing samples, the accuracy of the models remarkably drops. The percentage of correct predictions obtained by the NN model is less than 74%, while that obtained by the MNL model is less than 4%. Furthermore, the KS test reflects differences in the prediction results of the two models.

For modelers, it is essential to check the over-fitting problem of the proposed model, especially for models with many parameters. The over-fitting problem is defined as the infeasibility of generalizing to other situations owing to adaptation to a particular situation. In addition, the over-fitting problem in a multilayer perceptron NN model is identified in (Mozolin et al. 2000). For this purpose, the models discussed in this study are validated by dataset 2.

For non-lane-changing samples, the two models still perform well. The percentage correctly predicted for left and right lane-changing samples declines to 72.4% and 46.43% in the NN model, whereas the MNL model is totally unable to predict lane-changing decisions. Moreover, the performance of the two models is statistically different according to the KS test. It should be noted that although the accuracy noticeably drops, the over-fitting problem in these two models is not serious in light of the validation results in (Hunt and Lyons 1994) and our previous study on car-following models (Zheng et al. 2012a).

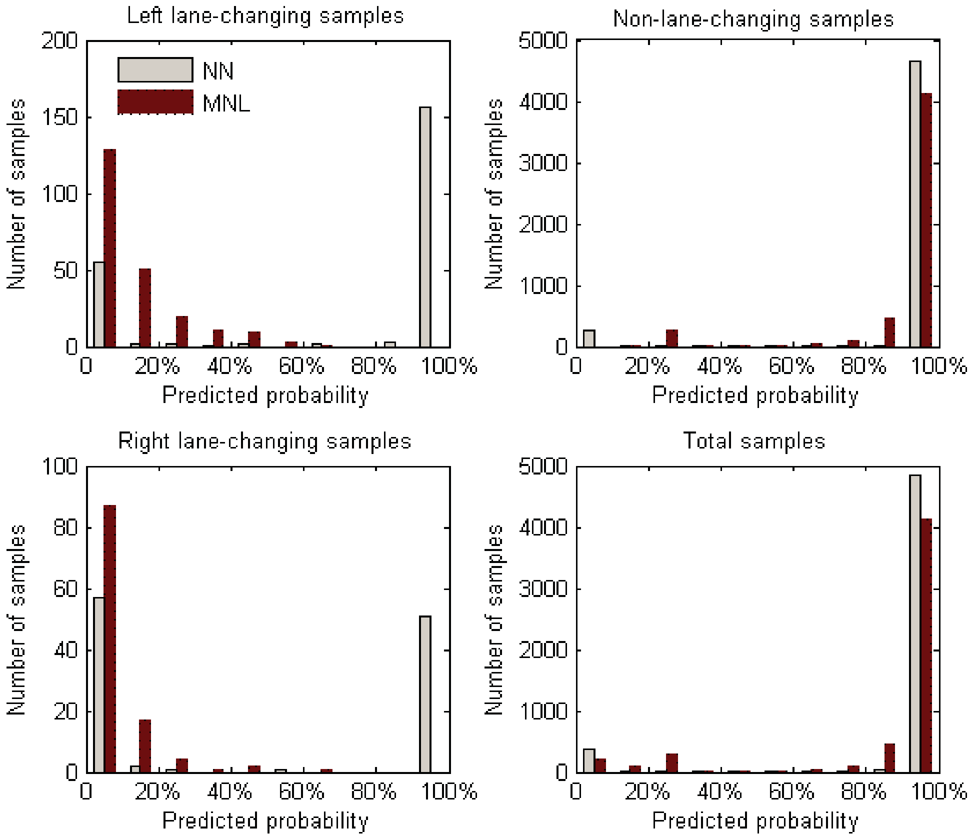

Fig. 6.5 Distribution of predicted probability for actual decisions in dataset 2

Table 6.5 Percentage of correct predictions in dataset 2

	Left lane-changing samples		Non-lane-changing samples		Right lane-changing samples		Total samples	
Number of samples	223		5030		112		5365	
	NN	MNL	NN	MNL	NN	MNL	NN	MNL
P > 33.3%	73.54%	9.42%	94.17%	94.04%	46.43%	2.68%	92.32%	88.61%
P > 50%	72.2%	1.79%	93.76%	93.96%	46.43%	0.89%	91.87%	88.18%
KS test	1		1		1		1	

In addition to reflecting the accuracy of the two models, the results in this section also suggest that validating the lane-changing model by total samples (Hunt and Lyons 1994) or macroscopic traffic characteristics (Sun and Kondyli 2010)appears to be insufficient, because the performance of the MNL model is also acceptable for all samples, but is poor for lane-changing samples.

6.6 Application

Despite accounting for only a small proportion of all vehicular traffic, heavy vehicles have a significant impact on traffic flow and traffic safety (Moridpour et al. 2010; Stuster 1999). Besides, as reported in (Aghabayk et al. 2011; Peeta et al. 2005), the number of heavy vehicles has markedly increased over the past few decades in North America and Australia, and this trend is likely to continue at least over the next decade. Owing to physical and operational characteristics, heavy vehicles impose physical and psychological effects on surrounding vehicles and drivers. From the common driving experiences, it is also known that most car drivers are unwilling to remain behind heavy vehicles during their trips owing to speed and visibility obstructions. In general, to mitigate the impact of heavy vehicles, car drivers may either maintain large distances or change lanes, which lead to a decreased capacity and additional driving risks. However, in literature, there are only a few studies that relate to the impact of heavy vehicles on lane-changing decisions. Because the vehicle type of surrounding vehicles is not incorporated in previous lane-changing models, such research can only be carried out by an in-vehicle survey (Sun and Elefteriadou 2012). Meanwhile, the NN model in this study provides a solution to quantitatively evaluate such an impact.

Using dataset 1, we first evaluate the impact of heavy vehicles on non-lane-changing decisions of car drivers. For non-lane-changing samples that are correctly predicted by the NN model and have the nearest lead vehicles (that are cars or motorcycles) in the current lane, we gradually increase the proportion of heavy vehicles by changing the vehicle type of the nearest lead vehicles in the current lane to be of the heavy vehicle type. By making such adaptations, the non-lane-changing decisions may be changed and the proportion of changed decisions can be calculated by the NN model. In the same way, for left/right lane-changing samples that are correctly predicted by the NN model and have the nearest lead vehicles (that are cars or motorcycles) in adjacent lanes, we change the vehicle type of the adjacent nearest lead vehicles to be of the heavy vehicle type. This adaptation may lead to the rescission of some left/right lane-changing decisions. The impact of heavy vehicles on lane-changing and non-lane-changing decisions is displayed in Fig. 6.6.

From Fig. 6.6, it is clear that with the increase in the number of heavy vehicles in the current lane, non-lane-changing samples that decide to change lanes gradually increase. When the proportion of heavy vehicles is 50%, 3.44% of non-lane-changing samples decide to change lanes. If the nearest lead vehicles in the current lane are all heavy vehicles, the percentage of samples that change their decisions is more than 7%. For the left lane-changing samples, if 25% of the nearest lead vehicles in the left lane are heavy vehicles, more than 5% of the samples rescind their lane-changing decisions. When the nearest lead vehicles in the left lane are all heavy vehicles, the percentage of samples that change their decisions is more than 17%. Compared with the non-lane-changing and left lane-changing samples, the right lane-changing samples are observed to be more susceptible to the existence of heavy vehicles in the right lane. If the proportion of heavy vehicles is 50%, around 14% of samples decide to stay in the current lane. While the nearest lead vehicles in the right lane are all heavy vehicles, 26.5% of samples rescind their right lane-changing decisions. To some extent, the evaluation results are consistent with common driving experience, which also demonstrates the reasonability of the proposed model.

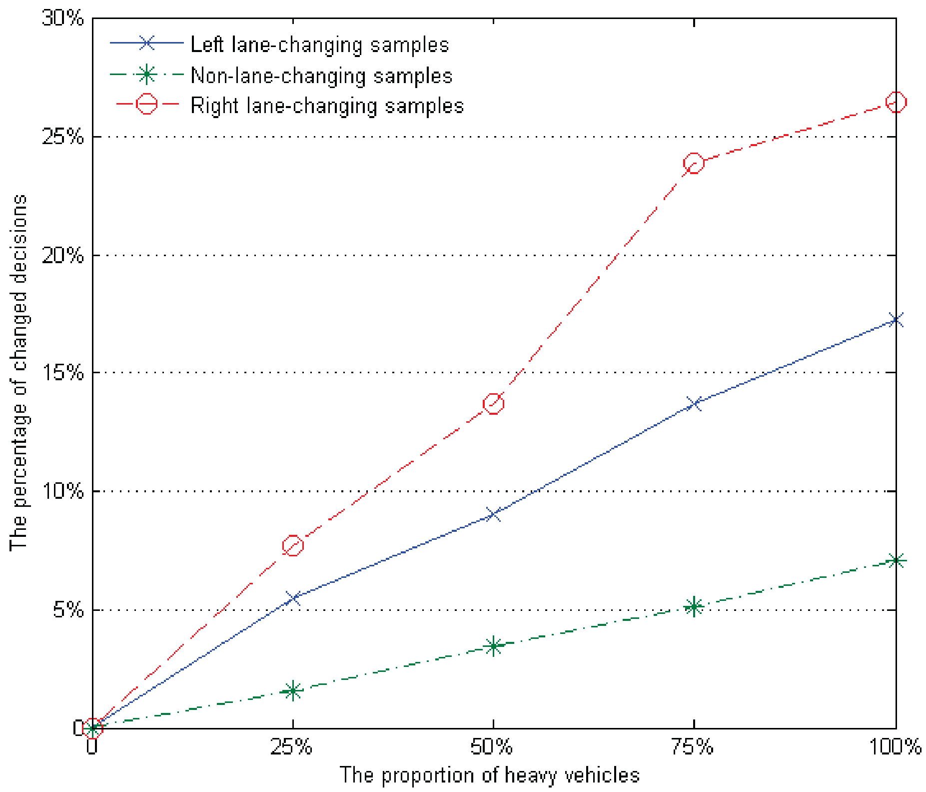

Fig. 6. 6 Impact of heavy vehicles on lane-changing and non-lane-changing decisions

6.7 Discussion

Although careful considerations were given in this study, there remain some issues that require further discussions. We discuss the generality of a model first, since it is one of the most important considerations when developing a model. Typically, a model consists of three components: the fundamental relationship between independent and dependent variables (linear or non-linear), the independent variables adopted in the model, and the parameters associated with the independent variables. According to the problem to be solved, modelers decide their preferred relationship between independent and dependent variables, and adopt the independent variables that are considered having significant impacts on the dependent variable. Before actual practice, modelers use the data collected in a specific context to calibrate the parameters of the model so that the model outputs are similar to the observed data, which is known as model estimation (or model calibration). Furthermore, it is necessary to know how general the proposed model is or how serious the over-fitting problem in the model is. With the calibrated parameters, data collected in a different context are usually used to test the model, which is called model validation. Here, if the period, the weather or the study site, etc, in a context is different from the one in which data for model estimation were collected, we define the context as a different or new context. In fact, as pointed out by a reviewer, the generality of a model could not be confirmed by testing it in some specific cases. Even though the model is general for some contexts, it may not be general for other contexts. However, as it is very difficult to prove the generality of a model from a strictly mathematical viewpoint, the model validation process is still meaningful in the sense that it examines the generality of a model in a new context. In this study, we also used a new dataset collected during the different period to validate the performance of the proposed NN model. From the results in Fig. 6.5 and Table 6.5, it is clear that in the new dataset the NN model is more general than the MNL model. To further test the generality of the model, we repeated the estimation and validation processes, by using dataset 2 for model estimation and dataset 1 for model validation. The results are listed in the following table. It is noted that for left lane-changing, Non-lane-changing, and Total samples, the prediction results are highly consistent with the results in Tables 6.4 and 6.5. However, for right lane-changing samples the accuracy of the model declines greatly. Because of the less number of right lane-changing samples in dataset 2, driver's right lane-changing decisions are not well learned by the NN model so that it is unable to predict the right lane-changing behavior in dataset 1. To some extent, the results confirm the generality of the proposed model.

Table 6.6 The repeated estimation and validation results

	Left lane-changing samples	Non-lane-changing samples	Right lane-changing samples	Total samples
Dataset 2				
Number of samples	223	5030	112	5365
P>33.3%	78.3%	99.5%	51.8%	97.6%
P>50%	78.3%	99.5%	51.8%	97.6%
Dataset 1				
Number of samples	332	5284	221	5826
P>33.3%	66.7%	98.2%	27.6%	93.8%
P>50%	66.7%	97.8%	27.2%	93.5%

Due to the lack of available data, the generality of the NN model is not examined by using the data collected in other contexts such as in a rainy day or on a study site with different road geometries.

In addition, drawing samples from continuous vehicle trajectories provides a feasible remedy for the problem caused by the small portion of lane-changing instances used in training the NN model. However, more care should be taken to determine an appropriate number of non-lane-changing samples. If the proportion of non-lane-changing samples is increased, the accuracy of the NN model is improved for all samples. Whereas, for lane-changing samples, a reduction in the accuracy of the prediction results is expected. A rigorous analysis is required to determine a more convincing method of drawing samples. Besides, according to a recent study (Tomar and Verma 2011), the lane-changing process can be viewed as a series of multiple distinct phases: the planning phase, the preparation phase, the crossover phase, and the adjustment phase. Moreover, the NNs are used to model the vehicle's lateral movements in the crossover phase (Tomar and Verma 2011; Ding et al. 2013). Obviously, the NN proposed in this study can be applied to the planning phase. We also note that these NNs are all typical feed-forward networks and the back-propagation algorithm is adopted for training. However, as shown in Fig. 6.3, the number of neurons used in the hidden layer has very significant impact on the performance of NN. In (Tomar and Verma 2011; Ding et al. 2013), a quantitative analysis of such impact is not carried out, and it is unknown how many neurons are adopted in their study.

6.8 Conclusions

Lane changes are very common in daily driving and have many implications for traffic capacity and traffic safety. However, literature associated with lane changing is not as comprehensive as that of car following. This is mainly caused by the inherent complexity of lane changing and a lack of large-scale trajectory data to analyze such behavior.

In this study, using the large-scale trajectory data from the NGSIM program, we investigated the discretionary lane-changing behavior of cars. Because lane-changing instances are greatly outnumbered by car-following and free-flow instances during a driver's journey, representative samples were drawn from two trajectory datasets. A detailed data analysis shows that for left lane-changing samples, traffic conditions in the left lane are clearly superior to the current lane and the right lane, while for right lane-changing samples, the superiority of the right lane is not so noticeable. This implies that left and right lane-changing decisions are asymmetric and incentivized by different motivations, which was seldom discussed in previous studies. Owing to the ability to deal with complex nonlinear systems, an NN model was adopted to predict lane-changing decisions. Meanwhile, an MNL model that was often accepted as a framework for lane changing in previous studies was also developed for comparison purposes. The two models were validated by two datasets. In the dataset used for model estimation, the percentage correctly predicted by the NN model is 94.6% and 73.3% for left and right lane-changing samples, respectively, while for the MNL model, the percent is only 13.3% and 3.3%, respectively. In the new dataset, the accuracy of left and right lane-changing samples in the NN model drops to 72.2% and 43.4%, respectively, but the MNL model is unable to forecast any lane-changing decisions. Obviously, the NN model outperforms the MNL model in this study. In addition, we investigated the impact of heavy vehicles on lane-changing decisions of car drivers using the sensitivity analysis of the proposed NN model. The results show that when the nearest lead vehicles in the corresponding lanes are all heavy vehicles, more than 7% of non-lane-changing samples decide to change lanes, more than 17% of left lane-changing samples reverse their left lane-changing decisions, and the percentage of the samples that changed their right lane-changing decisions is higher than 26.5%. Finally, in the discussion section some issues that are not considered in the current study are discussed.

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CHAPTER 7. CONCLUSIONS

This chapter summarizes the research reported in this thesis and highlights the major contributions. Directions for future research are suggested.

7.1 Research Summary

Owing to the ability to capture the complexity of traffic systems, traffic simulation has become one of the most widely used approaches for traffic planning, traffic design, and traffic management. Various traffic simulation software packages are currently available in the market, and they are utilized by thousands of consultants, researchers, and public agencies. With the popularity of traffic simulation, the car-following and lane-changing models, two of the most significant components in traffic simulation, have naturally attracted a lot of attention from traffic researchers. In this thesis, we also attempt to use some advanced computing technologies to model such driving behavior more realistically and accurately.

In Chapter 3, we first evaluated several typical car-following models by using field trajectory data and genetic-algorithm-based calibration method. The models with calibrated parameters are validated by using not only the uncongested traffic data but also congested traffic data. Unlike the results extracted from experimental data in (Brockfeld et al 2004; Ranjitkar et al 2005), there are obvious differences in performances of the evaluated models. Models with complex structure, such as SRM and OVM, cost more time than those with simple structure, such as NM and CAM, in simulation process, which means they are not suitable for real time traffic simulation. Besides, SRM and OVM do not perform as well as expected in terms of calibration and validation results. Furthermore, models with more parameters such as SDM are easy to incur over-fitting problem in validation process, although they can mimic real traffic accurately in calibration process. Even with the very simple structure, NM and CAM reproduce the real traffic well both in calibration and validation process, especially the discrete CAM, the only one that can survive in both validation processes.

Subsequently, a mixed logit model is proposed to describe drivers' acceleration and deceleration behavior in Chapter 4. Acceleration and deceleration are discretized into five alternatives. To represent different attractiveness of each alternative, alternative specific parameters are adopted in the model. Moreover, variables minus reference values are used, which improve explicability of the proposed model. Driving differences of different vehicle types are taken into account by the vehicle type variable in the model. In order to avoid interference of lane-changing behavior, this model is estimated and validated by trajectory data in HOV lane. The estimated parameters show reasonability of this model, and validation results sufficiently demonstrate robustness and accuracy of the model. Finally, the model is applied to simulate 30-minute traffic conditions. Simulation results exhibit that this model can describe driving differences of different vehicle types. Meanwhile, defects of this model in simulation process are also disclosed.

As reaction delay of the driver-vehicle unit varies greatly according to driver-vehicle characteristics and traffic conditions, and is an indispensable factor for modeling vehicle movements, in Chapter 5 we defined driver-vehicle reaction delay by the time interval not only between the relative speed and acceleration but also between the gap and speed of the vehicle. And, a neural network for instantaneous reaction delay is trained using samples observed from real traffic. Incorporating the reaction delay network into a neural-network-based car-following model, movements of nine vehicles which follow each other are simulated. Simulation results show that, for all discussed models, vehicle 2 is simulated with the highest accuracy, since the first vehicle is fed into simulation. This indicates that in previous studies validating the models by using the data only from one vehicle is insufficient. Moreover, we find that the performance of the models with instantaneous reaction delay is apparently better than that of the models with fixed delay. In the model with short fixed reaction delay, the simulated vehicles follow each other more closely than the observed vehicles do, and collisions occur in the model with long fixed delay, which also illustrates the necessity of taking into account instantaneous reaction delay in vehicle movement modeling. Besides, for future reference, the calibrated weights and bias in the neural-network-based reaction delay and car-following models are presented in Appendix.

Lane changes are very common in daily driving and have many implications for traffic capacity and traffic safety. However, literature associated with lane changing is not as comprehensive as that of car following. This is mainly caused by the inherent complexity of lane changing and a lack of large-scale trajectory data to analyze such behavior. In Chapter 6, using the large-scale trajectory data from the NGSIM program, we investigated the discretionary lane-changing behavior of cars. Because lane-changing instances are greatly outnumbered by car-following and free-flow instances during a driver's journey, representative samples were drawn from two trajectory datasets. A detailed data analysis shows that for left lane-changing samples, traffic conditions in the left lane are clearly superior to the current lane and the right lane, while for right lane-changing samples, the superiority of the right lane is not so noticeable. This implies that left and right lane-changing decisions are asymmetric and incentivized by different motivations, which was seldom discussed in previous studies. Owing to the ability to deal with complex nonlinear systems, a neural network (NN) model was adopted to predict lane-changing decisions. Meanwhile, a multinomial logit (MNL) model that was often accepted as a framework for lane changing in previous studies was also developed for comparison purposes. The two models were validated by two datasets. In the dataset used for model estimation, the percentage correctly predicted by the NN model is 94.6% and 73.3% for left and right lane-changing samples, respectively, while for the MNL model, the percent is only 13.3% and 3.3%, respectively. In the new dataset, the accuracy of left and right lane-changing samples in the NN model drops to 72.2% and 43.4%, respectively, but the MNL model is unable to forecast any lane-changing decisions. Obviously, the NN model outperforms the MNL model in this study. In addition, we investigated the impact of heavy vehicles on lane-changing decisions of car drivers using the sensitivity analysis of the proposed NN model. The results show that when the nearest lead vehicles in the corresponding lanes are all heavy vehicles, more than 7% of non-lane-changing samples decide to change lanes, more than 17% of left lane-changing samples reverse their left lane-changing decisions, and the percentage of the samples that changed their right lane-changing decisions is higher than 26.5%.

7.2 Main Contributions

The objective of this research is to improve modeling of driving behavior. This thesis contributes to the state-of-the-art in driving behavior modeling in the following aspects:

- In order to achieve a complete insight in the state-of-the-art of traffic modeling, several typical car-following models were evaluated by using trajectory data from real traffic conditions. Some interesting findings were provided.
- Drivers' acceleration and deceleration behavior was investigated by using a mixed logit model. Compared to conventional car-following models, the vehicle type variable is used in the proposed model, which enables the model to allow for driving differences of different vehicle types. In addition, the model was applied to simulate 30-minute traffic conditions. Simulation results confirm feasibility of simulating real traffic by the model.
- The driver-vehicle reaction delay was originally defined by the time interval not only between the relative speed and acceleration but also between the gap and speed of the vehicle.
- A neural network for instantaneous reaction delay was trained by observed delay samples and then compared with a previous piecewise linear reaction delay model. The NN reaction delay model is more realistic than the previous model.
- Incorporating the reaction delay network into a neural-network-based car-following model, movements of nine vehicles which follow each other are

simulated. Simulation results clearly illustrate the necessity of taking into account instantaneous reaction delay in vehicle movement modeling.

- For future reference, the calibrated weights and bias in the neural-network-based reaction delay and car-following models are presented in Appendix of Chapter 5.
- A detailed analysis of left and right lane changes is conducted, which suggests that the left and right lane changes are asymmetric and incentivized by different motivations.
- A neural network model that can completely account for the impact of surrounding vehicles on lane-changing decisions is developed. In addition, the proposed NN model clearly outperforms a multinomial logit model, which was frequently adopted as a framework for lane changing in previous studies, both in model estimation and validation processes.
- The impact of heavy vehicles on driver's lane-changing decisions was quantitatively evaluated using the sensitivity analysis of the proposed NN model.

7.3 Directions for Future Research

Although careful considerations were given in the studies of thesis, there remain some issues that require further discussions and we would like to suggest some directions for future research.

In Chapter 3, It is observed that although most models under study simulate real traffic with high fidelity in calibration process, in validation process none of them is able to perform as well as in calibration process. From this point of view, using different parameters or even different models under different traffic condition seems to be feasible for simulating real traffic more accurately. In fact, this view can be confirmed by only adjusting the parameter V_{max} in CAM to 14 in the second validation process. Accordingly, the error rate can be reduced from 49.20% to 38.79%.

We suggest that the model in Chapter 4 can be extended along two directions. In the study, we attempted to use the random alternative-specific constants to capture driving behavior variations across drivers. However, estimated results show that, except for the alternative 2, standard deviations of the specified normal distribution are not significantly different from zero. This means the proposed model is similar to the standard logit model. This model may be extended to capture such variations through specifying other random terms or a mixed error term (Bhat and Gossen 2004). Furthermore, lane-changing behavior can be integrated in the model by defining alternatives as in study (Antonini et al. 2006; Robin et al. 2009). We believe that each of the extensions of this model is a compelling and promising work.

In Chapter 5, we point out that due to lack of available data, the proposed methodology was not validated in some different contexts, such as in a rainy day. Typically, in different contexts the accuracy of the models will be reduced to some extent, if we still use the same parameters. In actual practice, we usually recalibrate the models by using the data collected in the corresponding context and adopt different W^1, b^1, W^2, b^2 in the Appendix. In addition, although more and more car-following and lane-changing models that can take a wide variety of driver-vehicle characteristics into consideration have been proposed so far, car-following and lane-changing behavior are usually treated individually. This is obviously inconsistent with the real driving behavior. A model framework that can integrate the acceleration and lane-changing behavior was developed in (Toledo et al. 2007), but some driver-vehicle characteristics were avoided, such as instantaneous reaction delay and lane-changing duration. By using the neural network technology, an integrated methodology for the vehicle two-dimensional movements (longitudinal and lateral) can comprise the further study.

In Chapter 6, drawing samples from continuous vehicle trajectories provides a feasible remedy for the problem caused by the small portion of lane-changing instances used in training the NN model. However, more care should be taken to determine an appropriate number of non-lane-changing samples. If the proportion of non-lane-changing samples is increased, the accuracy of the NN model is improved for all samples. Whereas, for lane-changing samples, a reduction in the accuracy of the prediction results is expected. A rigorous analysis is required to determine a more convincing method of drawing samples. Besides, according to a recent study (Tomar and Verma 2011), the lane-changing process can be viewed as a series of multiple distinct phases: the planning phase, the preparation phase, the crossover phase, and the adjustment phase. Moreover, the NNs are used to model the vehicle's lateral movements in the crossover phase (Tomar and Verma 2011; Ding et al. 2013). Obviously, the NN proposed in the study can be applied to the planning phase.

On the whole, data used in the thesis does include the drivers' characteristic, such as age, gender, driving experience etc and do not reflect the impact of the structure of roads on driving behavior. In future, such data should be collected to examine the proposed models. In addition, the proposed models should be incorporated in a traffic simulation software and tested in real application.

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