

## Research Article

# Driver's Lane Selection Model Based on Phase-Field Coupling and Multiplayer Dynamic Game with Incomplete Information

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Intelligent driving is an effective means to achieve the active safety of automobile, and the accurate prediction of vehicle group situation is the premise to achieve the intelligent driving of vehicle. Lane selection and lane changing are not only the most fundamental reasons for the transformation of vehicle group situation, but also the basic contents for the research on driver behavior of traffic flow theory. In this paper, with a view to the background of Internet of Things, the vehicle group situation was given a comprehensive consideration on the basis of the factors which influence driver's behavior. The driver's lane selection behavior was analyzed under the condition of incomplete information, and lane selection model based on phase-field coupling and multiplayer dynamic game with incomplete information was constructed considering the time-varying character of driving propensity. The means of actual driving experiment, virtual driving experiment, and microscopic simulation of traffic flow were used to verify the model. The verification results showed that the model built in this paper can objectively reflect the actual operation characteristic of traffic flow on road section and the process of lane selection. The theoretical basis of the research on lane selection can be provided for intelligent driving especially anthropomorphic driving under the condition of Internet of Things.

## 1. Introduction

With the rapid development of the transportation industry, the car ownership has increased rapidly. The contradiction among people, vehicle, and environment has become increasingly conspicuous, and the traffic safety is becoming more and more serious. Lane changing is one of the main factors affecting traffic safety, and lane selection which need drivers to analyze all kinds of information and consider a variety of factors in an instant is an important premise for lane changing, and the rationality of lane selection is directly related to driving safety. The multisource information of people-vehicle-environment can be collected and shared through Internet of Things, which can provide decision-making basis for driver's lane selection process and improve the active safety of driver and vehicle. Therefore, it is of great practical

significance to deeply study the lane selection behavior under the condition of Internet of Things. And the theoretical basis of the research on lane selection can be provided for intelligent driving, especially the anthropomorphic driving.

Many scholars have made sustained efforts to the research on lane changing model. Gipps [1] built a lane changing model to cover the urban driving situation, where traffic signals, obstructions, and heavy vehicles all exerted an influence. QI YANG et al. [2] and Ahmed K.I [3] divided the lane changing behavior into three parts, namely, producing an intention to change lane, detecting the conditions, and executing a lane change. M.Rickert et al. [4] presented a lane changing model based on cellular automata approach under two-lane traffic condition. The basic scheme of the model is to determine whether there is an obstacle in the lane where the target vehicle is located and whether there is enough gap

in the adjacent lane. Hidas [5] classified the maneuvers into free, forced, and cooperative lane changes under congested traffic conditions. And the lane changing model based on intelligent agent concept was developed. Mehdi Keyvan-Ekbatani et al. [6] investigated the decision process of lane changing maneuvers for a variety of drivers based on a two-stage test drive on freeways. Four distinct strategies were empirically found, namely, speed leading, speed leading and overtaking, lane leading, and traffic leading. Esmail Balal et al. [7] introduced a Fuzzy Inference System (FIS) which models a driver's binary decision to or not to execute a discretionary lane changing move on freeways. Yugong Luo et al. [8] proposed a dynamic automated lane change maneuver. The key technologies for this maneuver were trajectory planning and trajectory tracking. The planning problem was converted into a constrained optimization problem in the trajectory planning method, and a reference trajectory satisfying the demands of safety, comfort, and traffic efficiency was calculated and updated to complete the automated lane change and avoid the potential collisions. Shengbo Li et al. [9] presented a four-component framework to model, analyze, and synthesize a platoon of CAVs from the perspective of multiagent consensus control. The modeling technique of four-component framework was systematically introduced, the major performance metrics were discussed, and the design of distributed controller was presented.

Driving on the road is a dynamic game process, and many scholars have studied driver's lane changing behavior from the perspective of game theory. Hideyuki Kita [10] developed a two-person non-zero-sum noncooperative game theoretical model to describe the interactions of cars in merging or weaving sections and only the influence of through car on the behavior of a merging car was considered in the analysis. Both the merging and through cars would attempt to take the best actions for themselves by forecasting the other's action, respectively. Peng Jinshuan et al. [11] discussed a noncooperative mixed strategy game between the target vehicle and the following vehicle in the target lane and deeply analyzed the payoffs of the players and the Nash equilibrium. Alireza Talebpour et al. [12] put forward a two-person non-zero-sum noncooperation game model to analyze the interaction between the target vehicle and the following vehicle which is in the target lane. The lane changing models with complete and incomplete information were, respectively, established according to whether they were equipped with V2V communication. Zhang Yuanliang [13] proposed a discretionary lane changing model based on Stackelberg game and studied the game process of the target vehicle and the following vehicle in the target lane. Based on receding horizon optimal control and dynamic game theory, Meng Wang et al. [14] put forward a predictive approach for unified lane changing and car-following control. In the proposed approach, discrete lane change decisions and continuous accelerations were evaluated jointly to minimize the payoff function and obtain the Nash equilibrium solution.

The shortcomings of the previous studies on lane changing are mainly as follows. First, the driving propensity, especially the time-varying driving propensity is not fully considered in the previous studies. Driving propensity would

change with road environment and vehicle group situation. Different drivers are different in the aspects of expected speed, expected distance, weight preference of payoffs, and even the extent of information perception and mastery on traffic environment. Second, the vehicle types and multi-lane environment are seldom taken into consideration in the existing studies. Different vehicle types have different influences on drivers. And in the multilane environment, the composition of vehicle type proportion would be more complicated, the propensity type of driver would be more various, and the frequency of lane changing would be higher. Third, in the existing lane, changing model based on game theory, only the two-person static game model is constructed, which is between the vehicle to change lane and the following vehicle on target lane. The interactive influence of the two vehicles was analyzed, but the influences of lane selection strategies of surrounding vehicles were ignored. Fourth, the completeness degree of information the driver obtained is seldom considered in the previous lane changing model based on game theory. The completeness degree for drivers to learn and master the information would be different under the different development level of Internet of Things.

Aimed at the issues of the previous studies, the grouping vehicles driving on the urban expressway were chosen to be the research object and the vehicle group situation was analyzed under the background of Internet of Things. On this basis, driver's lane selection model based on phase-field coupling and multiperson dynamic game with incomplete information was constructed considering the influence of time-varying driving propensity. The payoff of every player was analyzed to obtain driver's lane selection strategy.

## 2. Method

Before constructing the lane selection model, the vehicle group situation was defined and its mathematical description was built. And the vehicle group situation types were identified after the division and reduction. Based on the game analysis of driver's lane selection behavior, the driver's lane selection model based on phase-field coupling and multiperson dynamic game with incomplete information was constructed.

*2.1. Vehicle Group Situation.* Traffic situation refers to the states and situations of all traffic entity deployment and behavior in the driver's interest-sensitive area (interest-sensitive area refers to an area which has a greater impact on vehicle safety and allocates more driver's attention), and it contains all the information of traffic entity [15, 16]. In this paper, vehicle group situation in which driver can perceive in the interest-sensitive area, including the characteristics of traffic entity and vehicle group relationship and also considering the macroscopic characteristics of density and speed, was taken as an example to research the driver's lane selection behavior.

*2.1.1. Definition of Vehicle Group Situation.* As shown in Figure 1, the three-lane condition on urban expressway was taken as an example, target vehicle  $n_1$  is chosen as the research

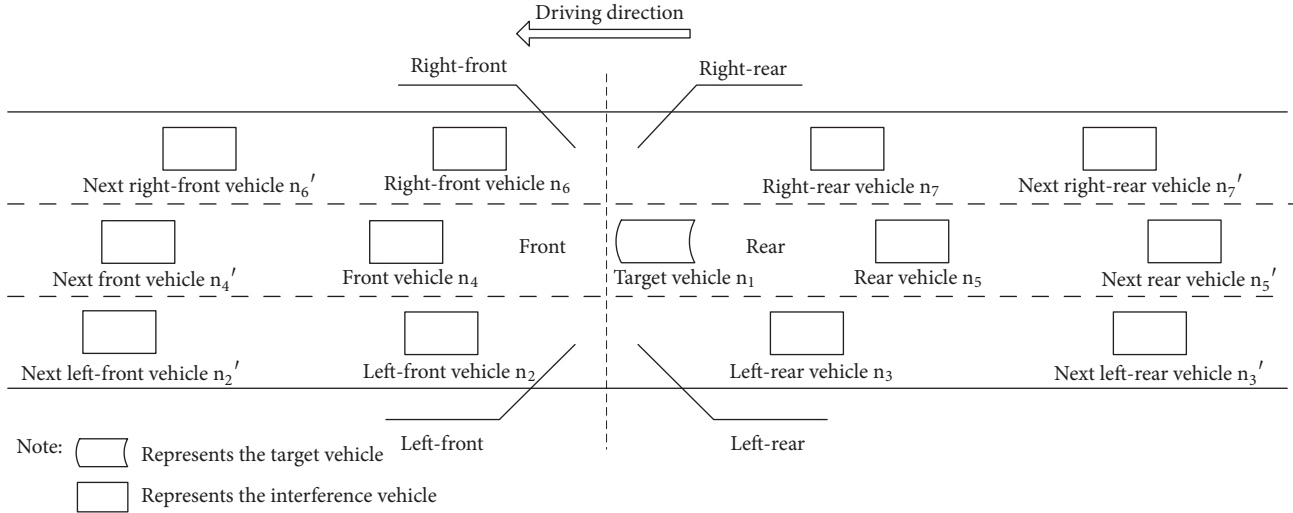


FIGURE 1: Vehicle group situation when target vehicle is located in the middle lane.

subject (unless otherwise specified, the case of target vehicle  $n_1$  located in middle lane is taken as an example), and the interest-sensitive area is divided into left-front, left-rear, front, rear, right-front, and right-rear subarea according to the position of target vehicle's front bumper. The target vehicle  $n_1$ , left-front vehicle  $n_2$ , left-rear vehicle  $n_3$ , front vehicle  $n_4$ , rear vehicle  $n_5$ , right-front vehicle  $n_6$ , and right-rear vehicle  $n_7$  were chosen as the game players to analyze and construct the driver's lane selection model. The next front or next rear vehicles would not be included in game player and they were only considered when calculating the driving payoffs.

**2.1.2. Mathematical Description of Vehicle Group Situation.** During driver's lane selection, generally, radical drivers focus on traffic efficiency, tend to change left, and mainly consider the average speed of vehicle; conservative drivers focus on comfort, tend to change right, and mainly consider the traffic flow density. So it is necessary for developing the mathematical description of vehicle group situation to take the two macroscopic parameters of density and speed into consideration. Meanwhile, in the microscopic aspect, the interactive influences with surrounding vehicles would be considered when the driver makes a decision on whether to change lane. The concept of "force" in the physics can be referenced and the description of interactive relationships among vehicles can be abstracted into interaction force. Thus, the vehicle group situation the target vehicle located in can be abstractly described through the set of lane force the target vehicle received in the vehicle group relationship. And if the vehicle in a subarea has a positive impact on the target vehicle to choose the lane in which the subarea is located, then the force is considered to be an attraction, and the converse effect is defined as repulsion. The effect size was used to describe the magnitude of force, and the effect size of the greatest repulsion was represented by -1, whereas the effect size of the greatest attraction was represented by 1 (Table 1).

The relationship among traffic flow parameters of traffic volume  $q$ , velocity  $v$ , and density  $\rho$  is  $q = v \cdot \rho$ . Combining the actual research, the traffic state of urban expressway is divided into three levels: smooth, slow, and congestion. And the corresponding classification of level of service is shown as Table 2.

The fuzzy logic method [17, 18] was used to grade the effect size, in which the vehicle type (Small, Middle, Large), relative distance (Danger, Near, Medium, Far), relative speed (Negative Large, Negative Small, Zero, Positive Small, Positive Large), traffic flow density of each lane (Small, Middle, Large), average speed of each lane (Large, Middle, Small), and the driver's propensity of target vehicle (Radical, Common, Conservative) were comprehensively considered. In the fuzzy logic method, the fuzzy variables, corresponding fuzzy sets, and the calculation of fuzzy subset boundary value can reference the literature [19]. Limited to the space, only one of the typical language fuzzy rules was listed as follows.

If the type of target vehicle is small, the type of left-rear vehicle is small, the driving propensity of target vehicle driver is radical, the relative distance between target vehicle and left-rear vehicle is far and their relative speed is positive large, the traffic flow density in left lane is small, and the average speed in left lane is large, then the effect size of left-rear vehicle acted on target vehicle is 1.

The force that left-rear vehicle acted on target vehicle can be obtained based on the above method. Similarly, the force that each vehicle in the interest-sensitive area acted on target vehicle and the force it received also can be obtained. The force set for target vehicle  $n_1$  can be expressed as  $f_1^0 = [\text{front vehicle force, rear vehicle force, left-front vehicle force, left-rear vehicle force, right-front vehicle force, right-rear vehicle force}] = [F_1^q, F_1^h, F_1^{zq}, F_1^{zh}, F_1^{yq}, F_1^{yh}]$ . Similarly, the force set  $f_i^0$  for other vehicles in interest-sensitive area also can be expressed in the same way.

Considering that the contribution rate of vehicles located in different areas was different, the contribution rate that

TABLE 1: Corresponding effect size of different forces.

| Force       | Strong repulsion | Middle repulsion | Weak repulsion | Zero | Weak attraction | Middle attraction | Strong attraction |
|-------------|------------------|------------------|----------------|------|-----------------|-------------------|-------------------|
| Effect size | $[-1, -0.7)$     | $[-0.7, -0.3)$   | $[-0.3, 0)$    | 0    | $(0, 0.3]$      | $(0.3, 0.7]$      | $(0.7, 1]$        |

TABLE 2: Classification of level of service for basic section on urban expressway.

| Level of service | Density (pcu/km/lane)        | Velocity (km/h)             | Maximum service volume (pcu/h/lane) |
|------------------|------------------------------|-----------------------------|-------------------------------------|
| Smooth           | $\rho \leq 32$ (Small)       | $v \geq 54.5$ (Large)       | 1600                                |
| Slow             | $32 < \rho \leq 50$ (Middle) | $40 \leq v < 54.5$ (Middle) | 2100                                |
| Congestion       | $\rho > 50$ (Large)          | $v < 40$ (Small)            | 2100                                |

target vehicle driver perceived can be regarded as the weight of corresponding force to calculate the force that each lane acted on target vehicle through the way of weighted summation. The contribution rates of vehicle in each subarea that the driver with different propensity types perceived could be obtained through the analytic hierarchy process based on the questionnaire survey. The result was shown as Table 4. In Table 4,  $\varepsilon_i^k$  represented the contribution rate of vehicle which is located in subarea  $k$  for target vehicle  $n_i$  ( $i = 1, 2, 3, 4, 5, 6, 7$ ). For example,  $\varepsilon_i^{ql}$  represented the contribution rate of the vehicle in front area for the target vehicle  $n_i$  when it located in the left lane. Therefore, the force of the lane that target vehicle  $n_1$  located was  $F_1^{lol} = f_1^q \varepsilon_1^q + f_1^h \varepsilon_1^h$ , the force of left lane was  $F_1^{zl} = f_1^{zq} \varepsilon_1^{zq} + f_1^{zh} \varepsilon_1^{zh}$ , the force of right lane was  $F_1^{yl} = f_1^{yq} \varepsilon_1^{yq} + f_1^{yh} \varepsilon_1^{yh}$ , and then the mathematical description of vehicle group situation that the target vehicle  $n_1$  located was  $F_1^0 = [F_1^{zl}, F_1^{lol}, F_1^{yl}]$ . Similarly, the vehicle group situation that other vehicles located also can be calculated.

**2.1.3. Division and Reduction of Vehicle Group Situation.** When the target vehicle is located on the left lane or right lane, the forces from the adjacent lane and the separated lane can be merged to obtain the force of side lane. Therefore, the vehicle group situation would be  $2^2 = 4$ ,  $2^3 = 8$ , and  $2^2 = 4$  types, respectively, when target is vehicle located in left, middle, and right lane, and totally be 16 types. The attraction is represented by “+”, and the repulsion is represented by “-”. Thus the 16 types of vehicle group situation are shown as Figure 2.

**2.1.4. Identification of Vehicle Group Situation.** The types of vehicle group situation at different moment needs to be identified due to the time-varying characteristics. The bases for the identification of vehicle group situation are spatial-time location of vehicles in interest-sensitive area and the force that target vehicle received. The identification process of the vehicle group situation that target vehicle located in under three-lane condition is shown as Figure 3.

**2.2. Driver's Lane Selection Model Based on Phase-Field Coupling and Multiperson Dynamic Game with Incomplete Information.** Game theory can analyze the situation with interactive influences among multiple persons. First, driver's

lane selection is a process of pursuing interests, such as driving safety, efficiency, and comfort. It is necessary for target vehicle driver to take the influences of lane selection strategies that its surrounding vehicle drivers have taken into consideration. And the multiperson dynamic game model needs to be constructed. Second, in the actual situation, there exist differences in the completeness degree of information and the usage of the interconnected devices the vehicle equipped. Therefore, the completeness degree of information that drivers could be obtained will be different. So it is necessary to study driver's lane selection behavior under the condition of incomplete information. Third, under normal circumstances, multiperson dynamic game is relatively complex and there not necessarily exists an equilibrium solution, often reaching the satisfaction state of each player. Thus, the satisfactory solution of the model can be solved. Fourth, driving preference, namely, the driving propensity, refers to the decision preference for lane selection under different vehicle group situations. Decision preference would be different for different types of driver and would change with the dynamic changes of vehicle group situation state. Therefore, in order to more accurately simulate the driving situations, the time-varying driving propensity should be considered during the model construction.

In conclusion, the model based on phase-field coupling and multiperson dynamic game with incomplete information can be constructed with the consideration of vehicle group situation and time-varying driving propensity to explore the driver's lane selection model adapted to the Internet of Things condition, especially the lane selection model for intelligent vehicles.

**2.2.1. Game Analysis of Lane Selection Behavior.** In Figure 1, vehicles  $n_1$ ,  $n_4$ , and  $n_5$  in middle lane had three behavior strategies, namely, *change left* (CL), *no changing* (NC), and *change right* (CR). Vehicles  $n_2$  and  $n_3$  in left lane had two behavior strategies, namely, NC and CR. And vehicles  $n_6$  and  $n_7$  in right lane had two behavior strategies, namely, NC and CL. In the actual game of lane selection, vehicles only equipped with partial interconnected devices, and only partial information about vehicle type, relative distance, relative speed, and the corresponding strategy space can be obtained. However, the information about the characteristics of other drivers and the corresponding driving payoffs cannot be obtained. Therefore, it is assumed in this paper that drivers

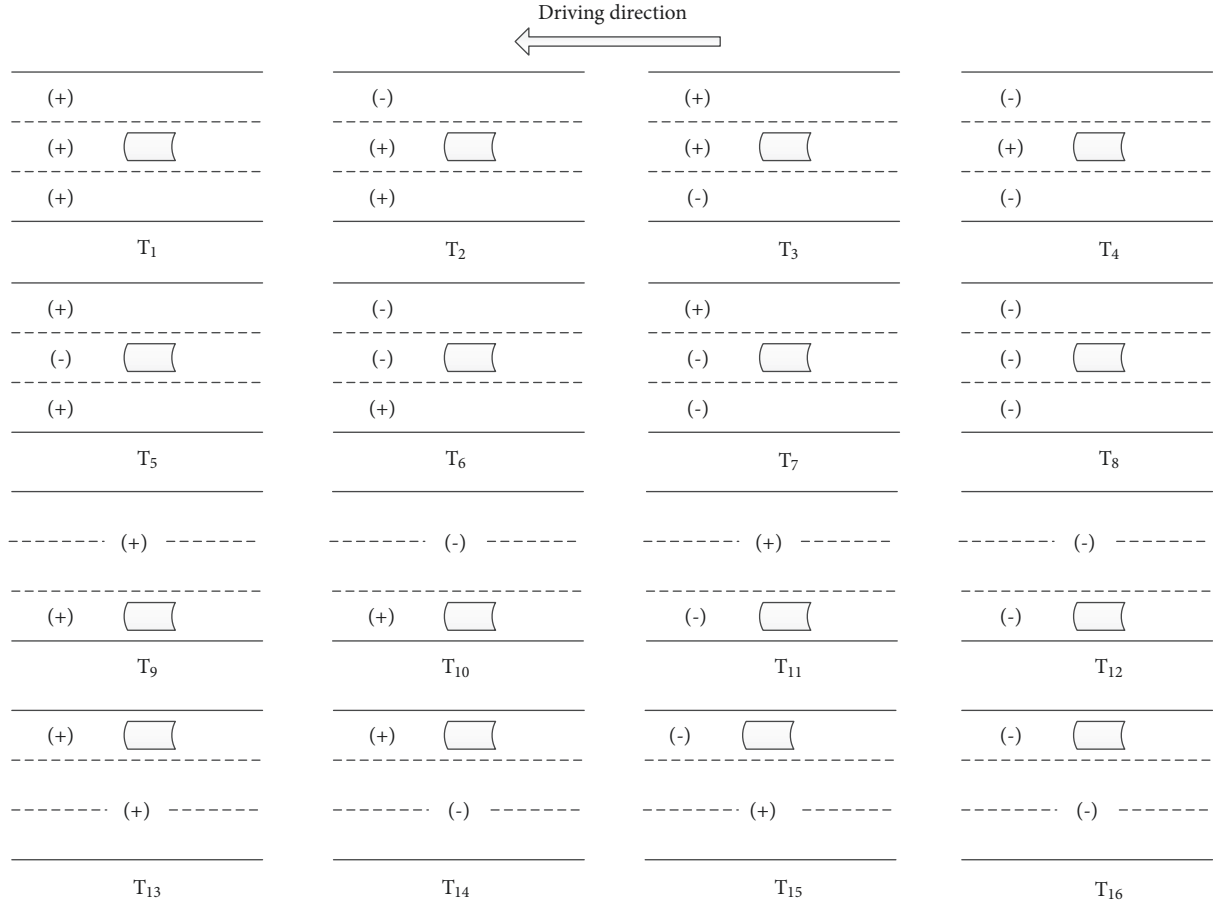


FIGURE 2: Reduction of vehicle group situation under three-lane condition.

involved in the lane selection game all get the incomplete information.

(1) *Determination on the Order for Drivers to Take Action.* In the process of dynamic game, the order for players to take action is successive, and the player who takes action later can obtain the information about the players who take action before him through observing their actions. And on this basis, the types of the players who take action before him are inferred and the prior probability distribution of their types is corrected, so as to choose his optimal action. Due to the fact that radical drivers are more likely to choose their own actions sooner than conservative drivers, and, compared to the vehicle at a rear position, the vehicle at a front position has the priority to take action. Thus, the order for drivers to take action is determined based on two indexes of the front or rear position in vehicle group relationship and radical degree of driver's propensity. Generally, drivers would have a higher priority to take action when their vehicles located at a front position and the driving propensity is more radical. The method in literatures [20, 21] was referenced to identify the driving propensity; the propensity type with the largest probability was chosen as the driver's propensity. The specific

process of the determination on the order for drivers to take action was shown in Figure 4.

(2) *Embedding of Hidden Markov Model.* The driver's propensity would be considered in every round of the game, and it will change with the environment, which would affect driver's consciousness and manipulation behavior and further affect the vehicle group situation. Therefore, the Hidden Markov model was established against the double stochastic process of vehicle group situation and driving propensity to explore the transformation mechanism of driving propensity. The detailed process refers to literature [22].

Finally, the formula for the optimized transformation probability of vehicle group situation is as follows:

$$\begin{aligned} \hat{a}_{ij} &= \frac{\sum_{t=1}^{L-1} P(x_t = T_i, x_{t+1} = T_j | u_1, \dots, u_L)}{\sum_{t=1}^{L-1} P(x_t = T_i | u_1, \dots, u_L)} \\ &= \frac{\sum_{t=1}^{L-1} \varepsilon_t(i, j)}{\sum_{t=1}^{L-1} \gamma_t(i)} = \frac{\sum_{t=1}^{L-1} a_{ij} b_j(u_{t+1})}{\sum_{t=1}^{L-1} \sum_{j=1}^{16} a_{ij} b_j(u_{t+1})} \end{aligned} \quad (1)$$

The optimization algorithm for the probability distribution of driver's propensity is as follows:

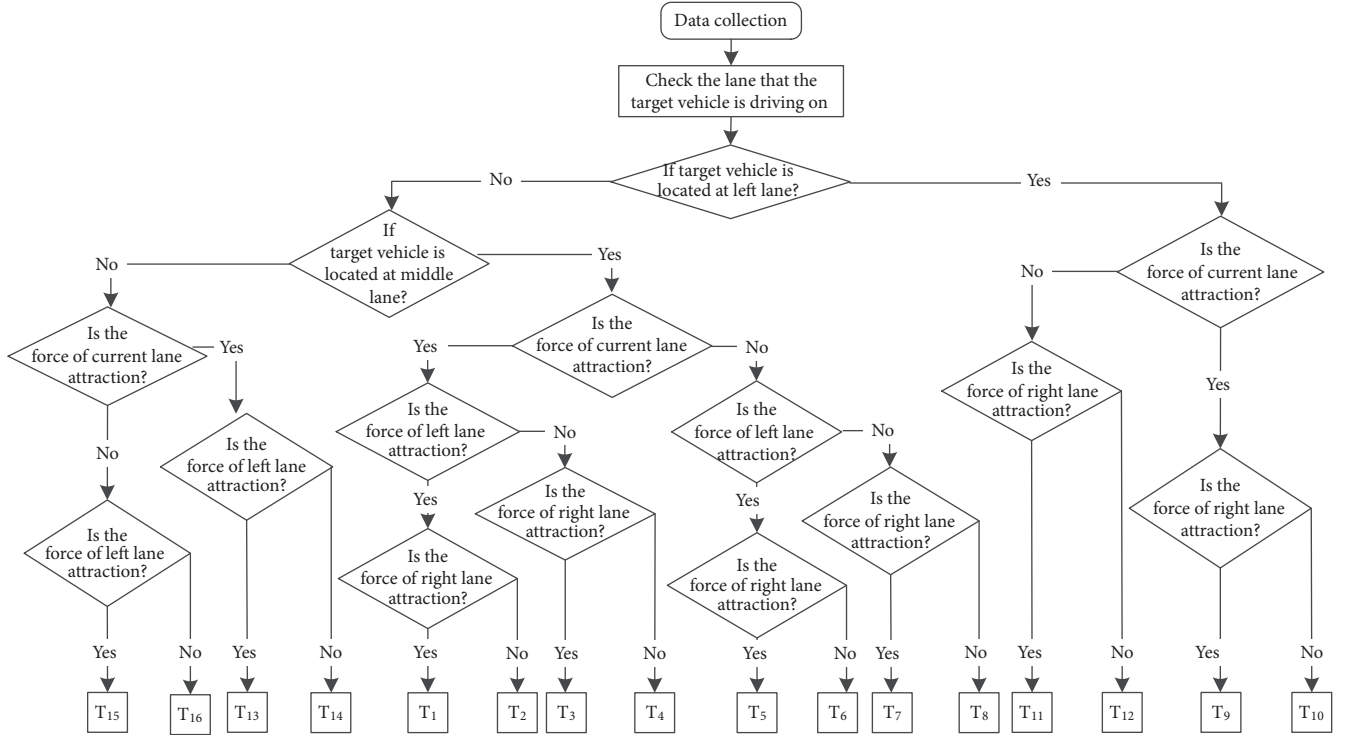


FIGURE 3: Identification flowchart of vehicle group situation under three-lane condition.

$$\hat{b}_j(u_k) = \frac{\sum_{t=1}^L P(x_t = T_j | u_1, \dots, u_L)}{\sum_{t=1}^L P(x_t = T_j | u_1, \dots, u_L)} \quad (2)$$

$$= \frac{\sum_{t=1}^L \gamma_t(j)}{\sum_{t=1}^L \gamma_t(j)} = \frac{\sum_{t=1}^L \alpha_t(j) \beta_t(j)}{\sum_{t=1}^L \alpha_t(j) \beta_t(j)}$$

The optimization algorithm for the probability distribution of the initial vehicle group situation state  $\pi_i$  is as follows:

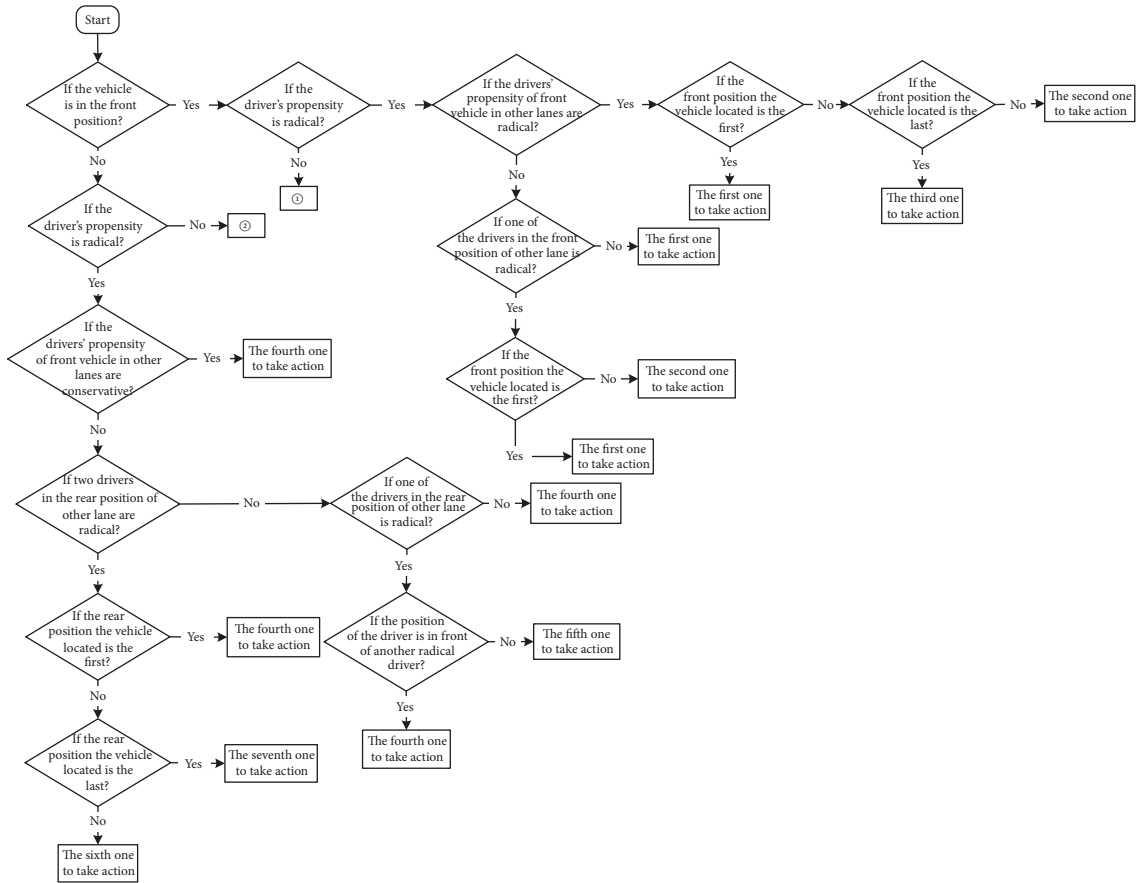
$$\hat{\pi}_1 = \gamma_1(i) = \frac{\alpha_1(i) \beta_1(i)}{\sum_{i=1}^{16} \alpha_1(i) \beta_1(i)} \quad (3)$$

(3) *Calculation of Driving Payoff.* Once the game strategies of players were selected, the situation of the game and the corresponding payoff function would be determined. The driving payoffs of driver's selection can be measured from the aspects of driving safety, efficiency, and comfort.

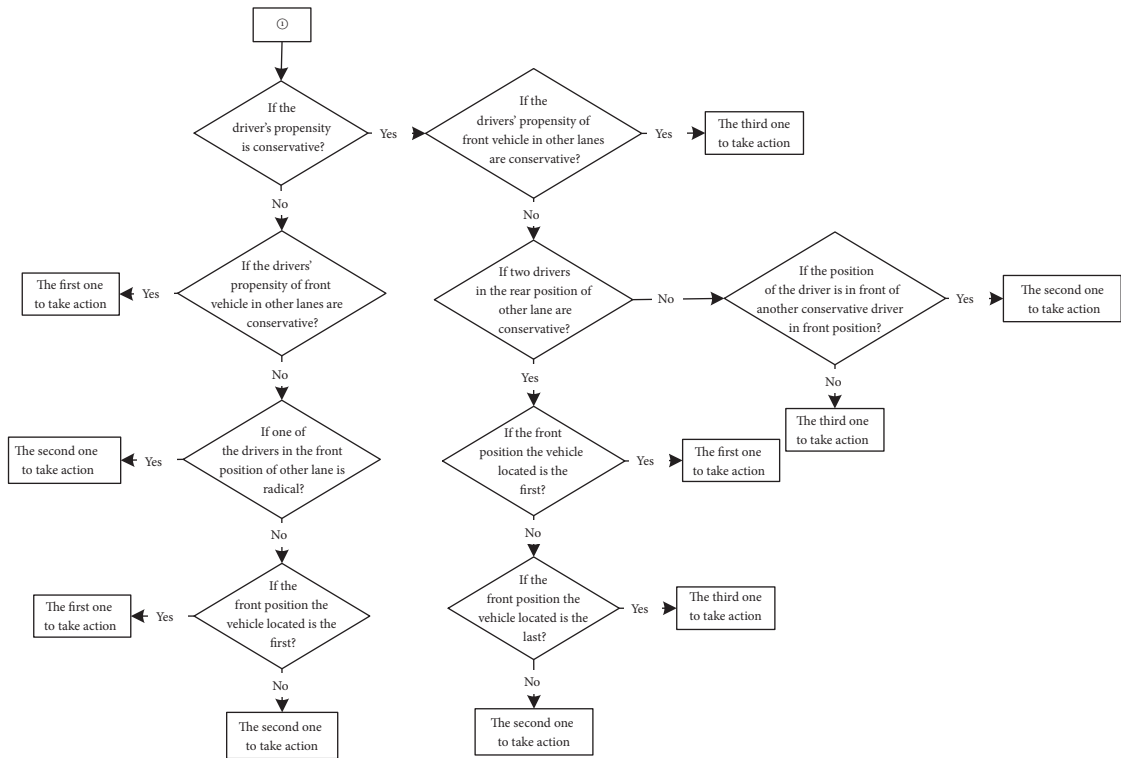
(a) *Calculation of Payoff on Driving Safety.* The payoff on driving safety (expressed by  $u_{n_1}^1$ ) refers to the change of the integrated force (the weighted summing of the forces that vehicle in each subarea acted on the target vehicle) that the vehicle got before and after executing the selected operation. The target vehicle  $n_1$  was chosen as an example, and the contribution rate (as shown in Table 3) that target vehicle perceived was donated as the weight of corresponding force that vehicles in each subarea acted on it. Before executing the selected operation, the integrated force that target vehicle

received was  $F_1 = f_1^q \varepsilon_1^q + f_1^h \varepsilon_1^h + f_1^{zq} \varepsilon_1^{zq} + f_1^{zh} \varepsilon_1^{zh} + f_1^{yq} \varepsilon_1^{yq} + f_1^{yh} \varepsilon_1^{yh}$ , and, after executing the selected operation, the integrated force  $F_1'$  also could be obtained in the same way. Then, the payoff on driving safety that target vehicle  $n_1$  obtained was  $u_{n_1}^1 = F_1' - F_1$ . Similarly, the integrated forces that vehicle in each subarea received before and after executing the selected operation, respectively, were  $F_i$  and  $F_i'$ , and the corresponding payoff on driving safety was  $u_{n_i}^1 = F_i' - F_i$ .

(b) *Calculation of Payoff on Driving Efficiency.* Payoff on driving efficiency (expressed by  $u_{n_1}^2$ ) can be represented in terms of the improvement on road traffic condition of the front area, and it can be measured through the difference between the integrated forces from the front area that vehicle received before and after executing the selected operation. The contribution rate (as shown in Table 3) that target vehicle perceived also was donated as the weight of corresponding force that vehicles in front area acted on it. Target vehicle  $n_1$  was chosen as an example; the integrated forces that target vehicle received before and after all drivers executed the selected operation, respectively, were  $F_f^1 = \sum \varepsilon_1^{qc} f_1^{qc}$  and  $F_{f'}^1 = \sum \varepsilon_1^{qc'} f_1^{qc'}$ . Then, the payoff on driving efficiency that target vehicle  $n_1$  obtained was  $u_{n_1}^2 = F_{f'}^1 - F_f^1$ , where  $f_1^{qc}$ ,  $\varepsilon_1^{qc}$ ,  $f_1^{qc'}$ , and  $\varepsilon_1^{qc'}$ , respectively, represented the force and the contribution rate of the vehicles in front subareas before and after executing the selected operation. Similarly, the integrated forces that vehicle in each subarea received before and after executing the selected operation, respectively, were  $F_f^i$

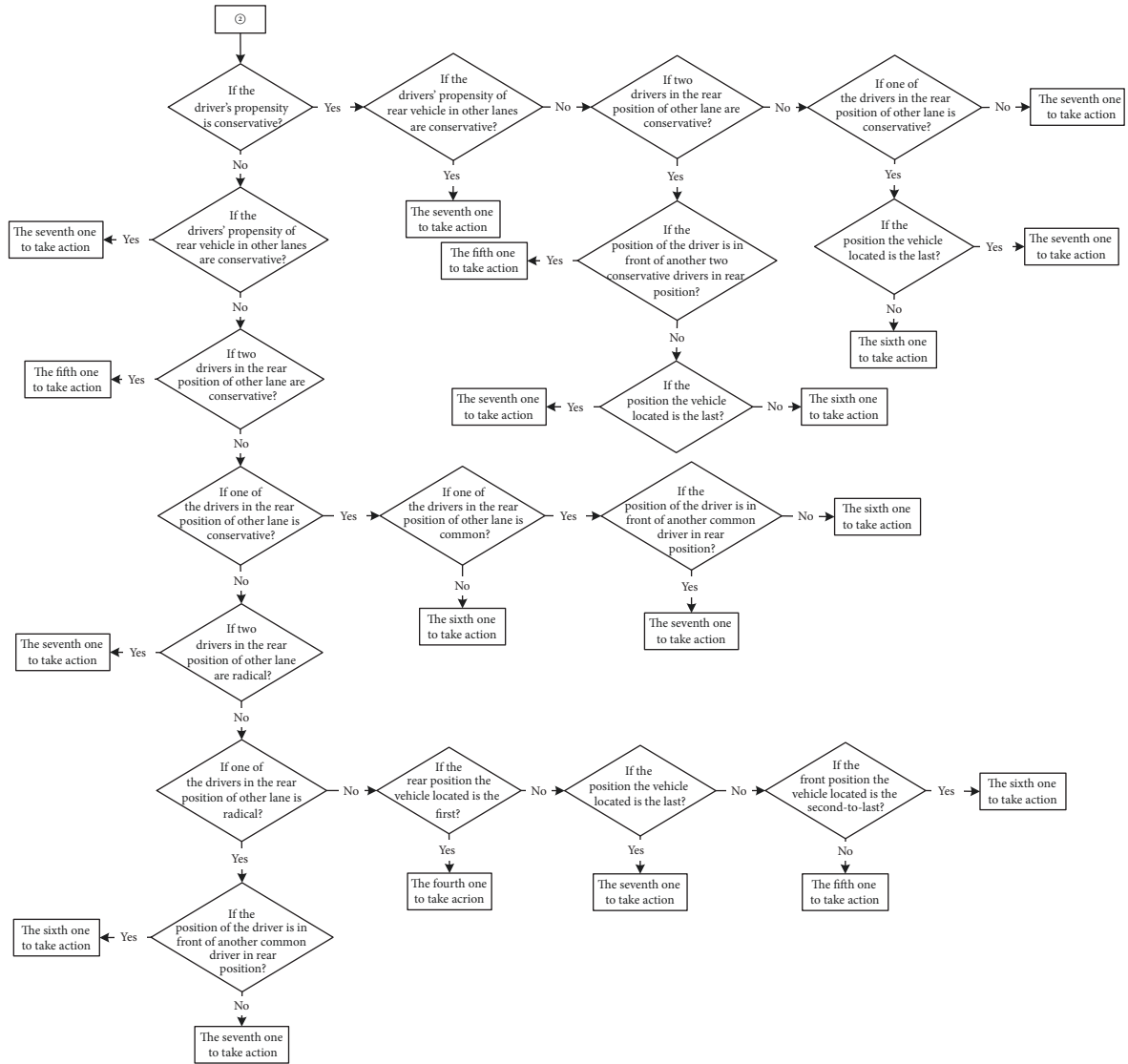


(a) Partial flow chart of the determination on the order for drivers to take action



(b) Partial flow chart of the determination on the order for drivers to take action

FIGURE 4: Continued.



(c) Partial flow chart of the determination on the order for drivers to take action

FIGURE 4: Flow chart of the determination on the order for drivers to take action.

and  $F_{f'}^i$ , and the corresponding payoff on driving efficiency was  $u_{n_1}^2 = F_{f'}^i - F_f^i$ .

(c) *Calculation on Payoff of Driving Comfort.* Payoff on driving comfort (expressed by  $u_{n_1}^3$ ) can be represented in terms of the difference between the forces that the lane the vehicle located acted on it before and after executing the selected operation, where the lane force included the cumulative force of the two vehicles in front of the vehicle in game and the force of the rear vehicle behind it, and the cumulative force referred to the sum of the forces that the front vehicle acted on the vehicle in game and the next front vehicle acted on the front vehicle. The contribution rate (as shown in Table 3) that target vehicle perceived also was donated as the weight of corresponding force that vehicles in front and rear areas acted on it. Therefore, the target

vehicle  $n_1$  was taken as an example, the forces that the target vehicle received from the lane it located before and after all drivers executed the selected operation, respectively, were  $F_o^1 = \varepsilon_1^q (f_1^q + f_4^q) + \varepsilon_1^h f_1^h$  and  $F_o'^1 = \varepsilon_1^{q'} (f_{1''}^{q'} + f_{4''}^{q'}) + \varepsilon_1^{h'} f_1^{h'}$ . Then, the payoff on driving efficiency that target vehicle  $n_1$  obtained after executing the selected operation was  $u_{n_1}^3 = F_o'^1 - F_o^1$ , where,  $\varepsilon_1^q$ ,  $\varepsilon_1^h$  and  $\varepsilon_1^{q'}$ ,  $\varepsilon_1^{h'}$  represented the contribution rate of the vehicles in front and rear subareas before and after executing the selected operation, respectively.  $f_1^h$  and  $f_1^{h'}$  represented the force that the vehicle in rear subarea acted on target vehicle  $n_1$  before and after executing the selected operation, respectively.  $f_{1''}^{q'}$  represented the force of the front vehicle  $n_{1''}$  acted on the target vehicle  $n_1$  after executing the selected operation and  $f_{4''}^{q'}$  represented the force of the next front vehicle  $n_{4''}$  on the front vehicle  $n_{1''}$ . Similarly, the forces



TABLE 3: Contribution rates from vehicles in each subarea, the different propensity types driver perceived.

| Target vehicle located in left lane   |                   |                   | Contribution rate  |                    |                    |                    |
|---------------------------------------|-------------------|-------------------|--------------------|--------------------|--------------------|--------------------|
| Propensity type                       | $\epsilon_i^{ql}$ | $\epsilon_i^{hl}$ | $\epsilon_i^{lyq}$ | $\epsilon_i^{lyq}$ | $\epsilon_i^{gyq}$ | $\epsilon_i^{gyh}$ |
| Radical                               | 0.246             | 0.153             | 0.186              | 0.228              | 0.088              | 0.099              |
| Common                                | 0.254             | 0.198             | 0.181              | 0.195              | 0.081              | 0.091              |
| Conservative                          | 0.265             | 0.226             | 0.175              | 0.171              | 0.078              | 0.085              |
| Target vehicle located in middle lane |                   |                   | Contribution rate  |                    |                    |                    |
| Propensity type                       | $\epsilon_i^q$    | $\epsilon_i^q$    | $\epsilon_i^q$     | $\epsilon_i^{zh}$  | $\epsilon_i^{yq}$  | $\epsilon_i^{yh}$  |
| Radical                               | 0.217             | 0.217             | 0.217              | 0.184              | 0.125              | 0.153              |
| Common                                | 0.224             | 0.224             | 0.224              | 0.164              | 0.136              | 0.134              |
| Conservative                          | 0.239             | 0.193             | 0.112              | 0.144              | 0.138              | 0.174              |
| Target vehicle located in right lane  |                   |                   | Contribution rate  |                    |                    |                    |
| Propensity type                       | $\epsilon_i^{qr}$ | $\epsilon_i^{hr}$ | $\epsilon_i^{lzq}$ | $\epsilon_i^{lzh}$ | $\epsilon_i^{gzq}$ | $\epsilon_i^{gzh}$ |
| Radical                               | 0.241             | 0.157             | 0.192              | 0.235              | 0.082              | 0.093              |
| Common                                | 0.245             | 0.189             | 0.189              | 0.218              | 0.075              | 0.084              |
| Conservative                          | 0.254             | 0.215             | 0.183              | 0.199              | 0.071              | 0.078              |

TABLE 4: Fuzzy weight of different payoffs that drivers with different types of propensity perceived.

| Type of driver | Fuzzy weight                          |                                           |                                        |
|----------------|---------------------------------------|-------------------------------------------|----------------------------------------|
|                | Payoff on driving safety $\omega_i^1$ | Payoff on driving efficiency $\omega_i^2$ | Payoff on driving comfort $\omega_i^3$ |
| Radical        | 0.35                                  | 0.5                                       | 0.15                                   |
| Common         | 0.4                                   | 0.35                                      | 0.25                                   |
| Conservative   | 0.5                                   | 0.2                                       | 0.3                                    |

that the lane the vehicle located acted on it before and after executing the selected operation, respectively, were  $F_o^i$  and  $F_{o'}^i$ , and the corresponding payoff on driving comfort was  $u_{n_i}^3 = F_{o'}^i - F_o^i$ .

Due to the differences of drivers with different types of propensity in the importance of cognition in terms of driving payoffs, for example, radical drivers pay more attention to the payoff on driving efficiency, and conservative drivers pay more attention to the payoff on driving safety. Therefore, the importance of cognition in terms of payoffs on driving safety, efficiency, and comfort can be donated as the fuzzy weight to give the corresponding payoffs, so as to measure the driving payoffs uniformly. The fuzzy weight of different payoffs that drivers with different types of propensity perceived was shown as Table 4. Therefore, the driving payoff for each driver in the game was  $u_{n_i} = \omega_i^1 u_{n_i}^1 + \omega_i^2 u_{n_i}^2 + \omega_i^3 u_{n_i}^3$  ( $i = 1, 2, \dots, 7$ ).

**2.2.2. Model Construction.** According to the game analysis of driver's lane selection, the lane selection model of the grouping vehicles based on multiperson dynamic game with incomplete information was constructed under three-lane condition.  $n_1, n_2, n_3, n_4, n_5, n_6$ , and  $n_7$  were chosen as the game players, and the dynamic game process of the grouping vehicles was as follows.

At time  $t$ , the vehicle group situation was identified according to the method in part 1.1.4, and driver's propensity was identified according to the method in [19, 22]. In the first round, the order for drivers in the vehicle group situation to take action was determined according to the identified

front or rear position of vehicle and the radicalness of the driver's propensity. Then, in each secondary round, the driver who was to take action would choose his own lane selection strategy according to the current vehicle group situation, the strategies of drivers who had taken action, and the prediction of the strategies for drivers who would take action after him. After driver's lane selection in every secondary round, the vehicle group situation needed to be reidentified according to the method in part 1.1.4. And the transformation of driver's propensity needed to be studied based on the embedded Hidden Markov model due to the interaction relationship between vehicle group situation and driving propensity. Meanwhile, according to the order, the driver who was to take action would choose his own lane selection strategy according to the current vehicle group situation, the strategies of drivers who had taken action, and the prediction of the strategies for drivers who would take action after him. Repeat the process of driver's lane selection, identification of vehicle group situation, and transformation of driving propensity until all drivers in vehicle group situation have selected the lane to drive on. After all drivers in the vehicle group situation have chosen their lane selection strategies, it was judged according to the requirements of game stopping time whether the present game met the requirements, where the requirements of game stopping time include three aspects: safety requirement, namely, judging whether the current integrated force the vehicle received from the vehicles in each subarea is greater than or equal to zero; efficiency requirement, namely, judging whether the difference of the integrated force from the front area at current and initial moment is greater than or

TABLE 5: Main microscopic parameters obtained from data preprocessing.

| Relative distance between target vehicle and surrounding vehicle ( $m$ ) |                    |                   |               |              |                     |                    |
|--------------------------------------------------------------------------|--------------------|-------------------|---------------|--------------|---------------------|--------------------|
| Data                                                                     | Left-front vehicle | Left-rear vehicle | Front vehicle | Rear vehicle | Right-front vehicle | Right-rear vehicle |
| Parameter                                                                | $\Delta d_2$       | $\Delta d_3$      | $\Delta d_4$  | $\Delta d_5$ | $\Delta d_6$        | $\Delta d_7$       |
| Relative speed between target vehicle and surrounding vehicle ( $m/s$ )  |                    |                   |               |              |                     |                    |
| Data                                                                     | Left-front vehicle | Left-rear vehicle | Front vehicle | Rear vehicle | Right-front vehicle | Right-rear vehicle |
| Parameter                                                                | $\Delta v_2$       | $\Delta v_3$      | $\Delta v_4$  | $\Delta v_5$ | $\Delta v_6$        | $\Delta v_7$       |

TABLE 6: Parameter calibration of lane selection model.

| Parameter    | $V_1$ | $V_2$ | $V_3$ | $V_4$ | $D_1$ | $D_2$ | $D_3$ | $D_4$ |
|--------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Radical      | -3.3  | -1.6  | 1.6   | 3.3   | 8.2   | 22.5  | 36.7  | 51.3  |
| Common       | -4.8  | -2.5  | 2.5   | 4.8   | 12.6  | 25.8  | 40.1  | 60.5  |
| Conservative | -8.4  | -4.5  | 4.5   | 8.4   | 22.3  | 38.3  | 54.4  | 70.4  |

equal to zero; comfort requirement, namely, judging whether the force the vehicle received from the lane it located is greater than zero. When it cannot meet the requirements of game stopping time, the vehicle group situation at current moment would be reidentified and the transformation of driver's propensity would be studied based on the embedded Hidden Markov model, so as to redetermine the order for drivers to take action. And then, a new round lane selection game would be conducted according to the game rules of the previous round until the requirements of stopping time can be satisfied after the end of the game at round  $N$ . Then, the lane selection strategy and the corresponding driving payoff of drivers at time  $t$  would be obtained, namely, the lane selection strategy at each round of game. After that, the simulation clock would be promoted to the time  $t + 1$ , and a new round lane selection game would be conducted. The process of driver's lane selection game was shown in Figure 5.

### 3. Results

The model parameters were calibrated after processing the experiment data. And on this basis, the model solution was obtained and so the driver's lane selection strategy.

**3.1. Data Processing and Model Calibration.** The vehicle trajectory sets of the section I-80 at the duration of 4:00-4:15 pm and the section US-101 at the duration of 7:50-8:05 am in the Next Generation Simulation (NGSIM) data set were selected to calibrate and validate the model constructed in this paper, where, the vehicles running on the lanes with the lane IDs 2, 3, and 4 were chosen as study subjects when entering into the data collection area (the most left lane ID was 1 on the driving direction and the number would increase successively to the right). The vehicles in HOV lane and other auxiliary lanes (the driving behavior is different from that in other lanes) and the continuous lane changing (the continuous lane changing is more likely the mandatory lane changing) would not be taken into consideration. Lane distribution diagrams of the studied sections I-80 and US-101 were shown in Figure 6.

**3.1.1. Data Processing.** Each record of NGSIM trajectory data contains not only the status information of a single

vehicle at a moment including the lane driving on, vehicle location, instantaneous speed, instantaneous acceleration, and so on but also the ID of preceding and following vehicle at the current moment. Therefore, the status information of the surrounding vehicle at the current moment and a certain interval moment can be queried according to the combination of video, vehicle ID, and time information. The vehicle type, relative distance, and relative speed in the vehicle group situation can be got through the combination of the obtained information, and the microscopic parameters which meet the calculation need of vehicle group situation can be obtained finally. The main microscopic parameters obtained from the data preprocessing of NGSIM are shown in Table 5 [23].

**3.1.2. Calibration of Lane Selection Model.** Based on the empirical value and the scientific analysis and process of the vehicle trajectory data set for I-80 section, the model parameters were calibrated through the repeated training and expert opinion. The calibration of the partial model parameters was shown in Table 6.

**3.2. Solution of Lane Selection Model.** According to the game analysis and the dynamic game process of driver's lane selection, at time, when the game reached the end of the round  $N$ , if all drivers in vehicle group situation got their own relatively satisfied driving states and the requirements of game stopping time can be reached from the aspects of safety, efficiency, and comfort. Then, vehicles in the grouping situation would keep a relatively stable driving state at this time, and driver's lane selection game would end at this time. The game analysis of driver's lane selection was referenced and the calculation about the requirements of game stopping time was as follows.

Safety requirement is to judge whether the integrated force  $F_i^n = \sum f_i^{k^n} \varepsilon_i^{k^n}$  that vehicle  $n_i$  received from the vehicles in each subarea at the end of round  $n$  ( $n = 1, 2, \dots, N$ ) is greater than or equal to zero. Efficiency requirement is to judge whether the difference  $F_{f^n}^i - F_f^i$  of the integrated force vehicle  $n_i$  received from the front area at the end of round  $n$  ( $n = 1, 2, \dots, N$ ) and the initial moment (namely,

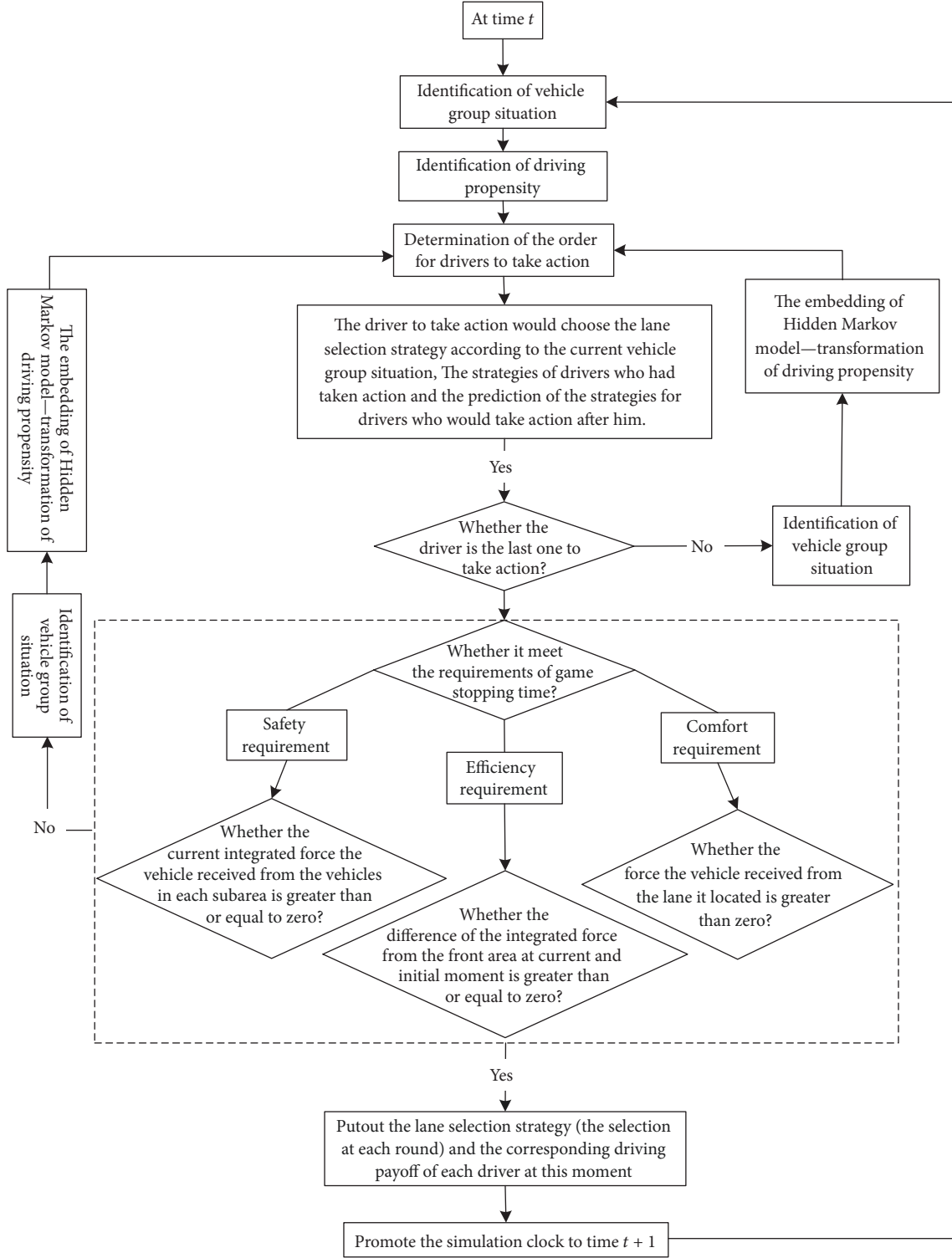


FIGURE 5: Process of driver's lane selection game.

$F_{fn}^i = \sum \varepsilon_i^{qc^n} f_i^{qc^n}$  and  $F_f^i = \sum \varepsilon_i^{qc} f_i^{qc}$ ) is greater than or equal to zero. Comfort requirement is to judge whether the force  $F_{on}^i = \varepsilon_i^{qn} (f_{in}^{qn} + f_{in}^{qn}) + \varepsilon_i^{hn} f_i^{hn}$  that vehicle  $n_i$  received from the lane it located at the end of round  $n$  ( $n = 1, 2, \dots, N$ ) is greater than zero.

When the game was over, the lane selection strategy and the corresponding payoff of each driver in vehicle group situation can be obtained according the process of game, and the lane selection strategy was the choice in each round of game. According to the game analysis, payoff of driving safety

TABLE 7: Model verification results.

| Lane ID | Prediction times | Comparison between prediction and actual results |                | Accuracy |
|---------|------------------|--------------------------------------------------|----------------|----------|
|         |                  | Agree times                                      | Disagree times |          |
| 2       | 50               | 41                                               | 9              | 82.00%   |
| 3       | 150              | 127                                              | 23             | 84.67%   |
| 4       | 150              | 131                                              | 19             | 87.33%   |
| Total   | 350              | 299                                              | 51             | 85.43%   |

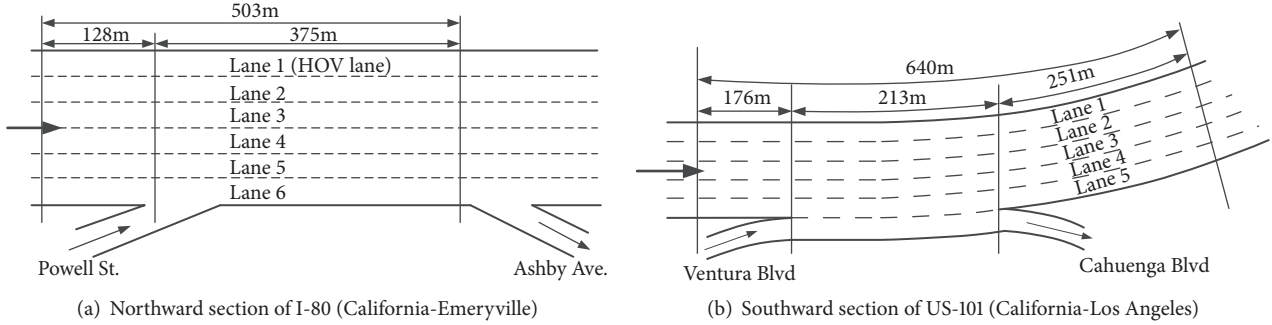


FIGURE 6: Lane distribution diagrams of the studied sections.

was  $u_{n_i}^1 = F_i^N - F_i^0$ , payoff of driving efficiency was  $u_{n_i}^2 = F_{f^N}^i - F_f^i$ , and payoff of driving comfort was  $u_{n_i}^3 = F_{o^N}^i - F_o^i$ . The driving payoff of each driver at the end of the game after round N was  $u_{n_i} = \omega_1^1 u_{n_i}^1 + \omega_2^2 u_{n_i}^2 + \omega_3^3 u_{n_i}^3$  based on the importance of cognition in terms of driving payoffs.

## 4. Discussions

The efficiency of the model was verified through experiment and simulation. And based on the verification results, the strength and weakness of the constructed model over existing methods were compared.

**4.1. Verification of Lane Selection Model.** The means of actual driving experiment, virtual driving experiment, and microscopic simulation of traffic flow were used to verify the constructed model.

**4.1.1. Verification of Lane Selection Model Based on NGSIM Trajectory Data.** The vehicle trajectory data of US-101 collected through NGSIM program was used to verify the model. Driver's lane selection model constructed in this paper was applied to analyze and process the video information and vehicle trajectory data collected from the studied road section and further to predict the driver's lane selection on the target lanes. The lane changing of vehicle was selected as the index to examine the prediction results of the driver's lane selection because that it is obvious and easy to observe for vehicle's status when driver selected the strategy of "CL" or "CR". The prediction results were compared with the actual lane changing situations to verify the validity of the model and the comparison results were shown in Table 7.

**4.1.2. Verification of Lane Selection Model Based on Actual Driving Experiment.** The road section of Yuanshan Road between Xincun West Road intersection and Renmin West Road of Zibo city, Shandong province, was selected as the experimental route. The experiment was conducted between 7:30 am and 9:30 am of normal working day with the good condition of weather and road and the traffic flow was nonfree flow. The overall length of the studied road section was 1.2km, as shown in Figure 7. Based on the video monitoring, 30 drivers with different driving propensities were chosen to conduct the experiment, and the experimental equipment was shown in Figure 8. During the experiment, the information of road, traffic, and environment was collected and the experimental data was stored. After the experiment, the lane selection model based on multiplayer game built in this paper was used to analyze and process the collected data. The effectiveness and validity of the model could be judged through comparing the prediction results with the actual lane selections recorded in the video (Figure 9). The results of actual driving experiment were shown in Table 9.

**4.1.3. Verification of Lane Selection Model Based on Interactive Parallel Driving Simulated Experiment.** In order to verify the model, the multichannel interactive parallel driving simulation system was used to conduct the virtual driving experiment, as shown in Figure 10. In this confirmatory experiment, the same traffic scene of virtual reality was constructed according to the road environment of actual driving experiment. Before the experiment, 20 drivers who participated in the experiment were trained in the driving simulator. During the experiment, the experimental data was stored and the whole video was recorded with the interference

TABLE 8: Comparison between prediction and actual lane selection result for driving simulation experiment.

| Driver's number | Prediction times (time) | Comparison between prediction and actual results |                       | Accuracy |
|-----------------|-------------------------|--------------------------------------------------|-----------------------|----------|
|                 |                         | Agree times (time)                               | Disagree times (time) |          |
| 1               | 90                      | 75                                               | 15                    | 83.33%   |
| 2               | 90                      | 79                                               | 11                    | 87.78%   |
| ...             | ...                     | ...                                              | ...                   | ...      |
| 9               | 90                      | 76                                               | 14                    | 84.44%   |
| 10              | 90                      | 78                                               | 12                    | 86.67%   |
| ...             | ...                     | ...                                              | ...                   | ...      |
| 19              | 90                      | 75                                               | 15                    | 83.33%   |
| 20              | 90                      | 77                                               | 13                    | 85.56%   |
| Average         | 90                      | 77.25                                            | 12.75                 | 85.83%   |

TABLE 9: Comparison of microscopic simulation result and measured data.

| Evaluation index         | Measured value | Simulation value | error (%) |
|--------------------------|----------------|------------------|-----------|
| Average speed (m/s)      | 12.36          | 11.78            | 4.69      |
| Average density (veh/km) | 35.41          | 36.93            | 4.29      |



FIGURE 7: Experimental route.

for driver was avoided. The lane selection model based on dynamic game with incomplete information built in this paper was used to analyze and process the collected data, and the optimal strategy result for the driver was calculated and output. And then the calculation result was compared with the actual lane selection result of the driver in experiment, and the result of comparative analysis was shown in Table 8.

It can be seen from Table 8 that the integrating degree of prediction and actual lane selection result was high with the built lane selection model in driving simulation experiment, and the average accuracy of the model prediction could reach 85.83%.

**4.1.4. Verification of Lane Selection Model Based on Microscopic Simulation of Traffic Flow.** According to actual driving experiment, car-following model and lane changing decision-making model were built, respectively, based on the optimal control theory and fuzzy multiobjective decision theory. The experimental data of drivers with different driving propensity was input to the microscopic simulation model of lane selection that did consider (simulation 1) or did not consider (simulation 2) the dynamic game among

the drivers. To verify the effectiveness and validity of the model built in this paper, the simulation results in microscopic regularity (such as lane changing frequency and lane changing times) and macroscopic regularity (such as speed, density, traffic volume, and lane occupancy) of traffic flow were compared with the actual situations of actual driving experiment.

The verification results of traffic flow in microscopic aspect were shown in Figure 11, and it described the distribution of lane changing times under different traffic volume in three-lane traffic scene. As mentioned, simulation 1 was the case that considered the driver's lane selection game for real-time simulation, while simulation 2 did not.

The verification of traffic flow in macroscopic aspect mainly included the average speed, average density and lane utilization ratio, and the verification results were shown in Table 9 and Figure 12.

In Table 9, the average speed and average density were selected as the evaluation index to compare the simulation and measured values based on the data of actual driving experiment, and the model error was in the acceptable range.

Figure 12 is the simulation result of the relationship between traffic volume and lane utilization ratio under three-lane condition, where the full line represented the actual result of the relationship between traffic volume and lane utilization ratio and the dot represented the simulation result obtained from the microscopic simulation model considering the dynamic game of driver's lane selection. It can be seen from Figure 12 that the microscopic simulation model which considered the dynamic game of driver's lane selection could simulate the relationship between traffic volume and lane utilization ratio much better, which indicated that the model built in this paper had a higher accuracy and feasibility.

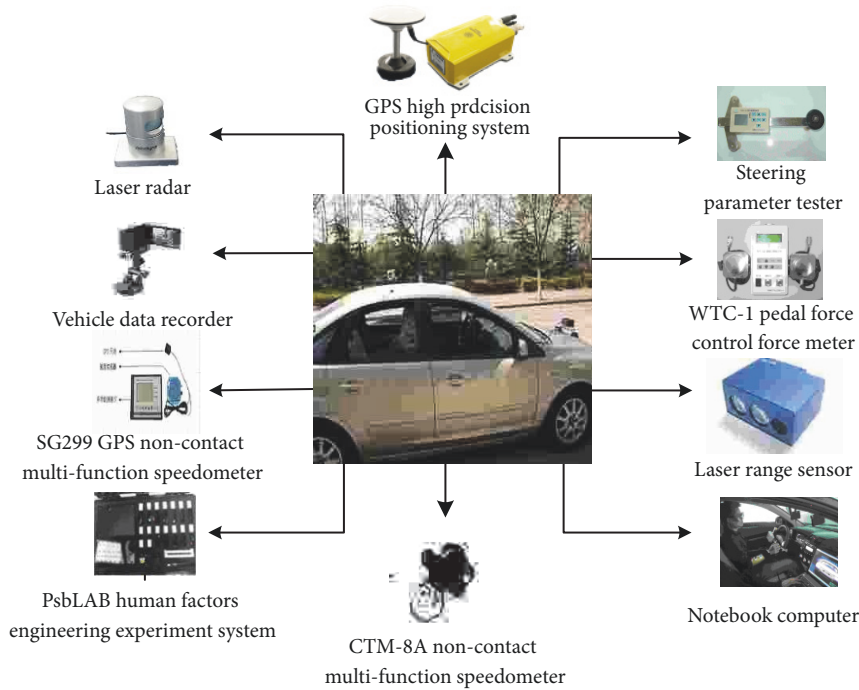


FIGURE 8: Information collection system of actual driving experiment.

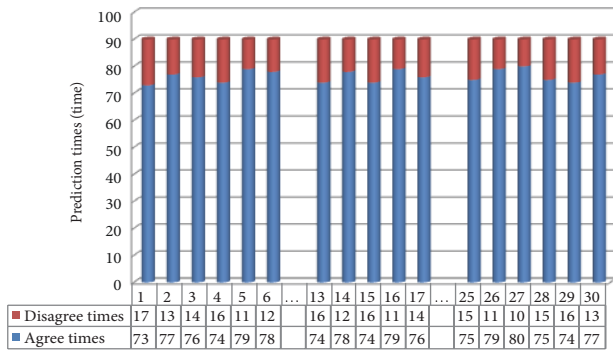


FIGURE 9: Comparison between prediction and actual results of actual driving experiment.

**4.2. Discussion.** The dynamic game model with incomplete information established in this paper comprehensively considered the factors which influence driver’s decision-making behavior, such as vehicle group situation, driving propensity, and the changing of preference. And it mainly analyzed driver’s lane selection behavior under the current condition of Internet of Things, especially the Internet of Vehicles.

Compared with the existing research on driver’s lane selection model, the proposed method is superior in the following aspects. First of all, the driving propensity was considered in the proposed method. And furthermore, the Hidden Markov model was embedded to study the transformation of driving propensity in order to take the influence of time-varying driving propensity into consideration. Second, the influence of the lane selection strategies for surrounding vehicles on target vehicle was considered rather than only

the influence of following vehicle on target lane. Third, the dynamic game model was constructed rather than static game model. Fourth, driving payoff was measured considering three aspects of driving safety, driving efficiency, and driving comfort, rather than only one aspect of driving safety.

However, the proposed method still has the following shortcomings. First, only one coupling relationship between vehicle group situation and driving propensity was considered when studying the transformation of driving propensity. However, different coupling relationship has different influence on the transformation of driving propensity. And the state of driving propensity (vehicle group situation) at time  $t + 1$  would be influenced by the state of vehicle group situation (driving propensity) at time  $t$ . Second, only the situation that vehicles equipped with partial interconnected devices and all drivers obtained the incomplete information was studied. And the problems of driver’s lane selection should be studied under the different penetration rate for vehicles equipped (or not equipped) with interconnected devices. Third, because of the differences of China and the United States in road condition and driving environment, there will be some error in model itself when applying the natural driving data (NGSIM data) for model calibration under the road condition of China; thus the model accuracy will be influenced. Fourth, to adapt to more complex traffic environments, the model needs to be extended to four or more lane scenarios and the game behavior of drivers in different road segments, such as intersections or ramps, needs to be comprehensively considered. In addition, driver’s moods and the infectivity of driving behaviors should be taken into consideration when constructing the model.

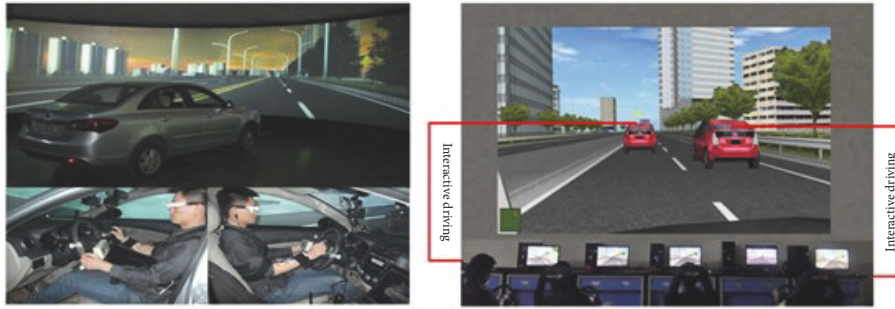


FIGURE 10: Driving simulation experiment.

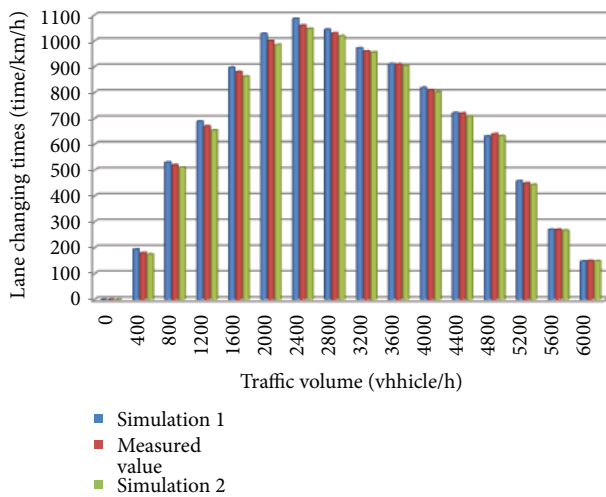


FIGURE 11: Comparison of lane changing times in simulated value and measured value under three-lane condition.

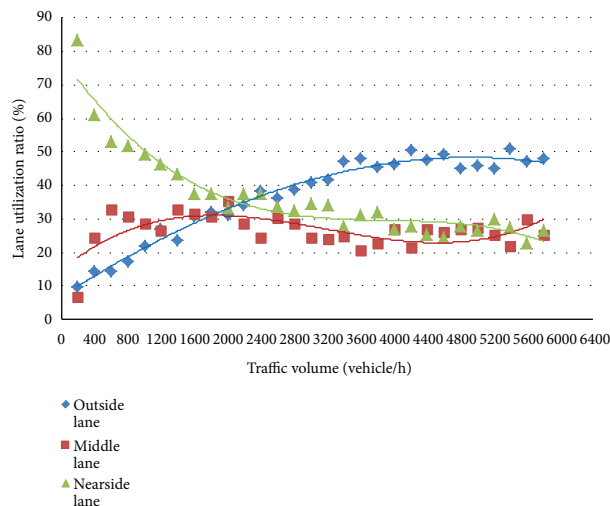


FIGURE 12: Simulation result of relationship between traffic volume and lane utilization ratio under three-lane condition.

### 5. Conclusion

In this paper, the game behavior of the grouping vehicles running on the urban expressway road section was analyzed, and

the factors which influence driver’s decision-making behavior such as vehicle group situation and driving propensity were comprehensively considered. The driver’s lane selection behavior was analyzed under the condition of incomplete information, and lane selection model based on phase-field coupling and multiplayer dynamic game with incomplete information was constructed considering the time-varying character of driving propensity. The driver’s lane selection strategy and the corresponding payoff were obtained through judging the stopping time and analyzing the process of the game. The means of actual driving experiment, virtual driving experiment, and microscopic simulation of traffic flow were used to verify the model. The verification results showed that the model built in this paper can objectively reflect the actual operation characteristic of traffic flow on road section and the process of lane selection. The theoretical basis of the research on lane selection can be provided for intelligent driving especially anthropomorphic driving under the condition of Internet of Things.

### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

### Acknowledgments

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