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Research on Traffic Vehicle Behavior Prediction Method Based on Game Theory and HMM

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ABSTRACT Traffic vehicle behavior prediction is a necessary prerequisite for intelligent vehicle behavior decision and trajectory planning. The behaviors of vehicles are deeply interactive. In order to reasonably predict the future behavior of traffic vehicles, based on the Game theory, this paper designs the behavior prediction framework of traffic vehicles, and establishes the GMM(Gaussian Mixture Model)-HMM(Hidden Markov Model) behavior recognition model. Then, the revenue function is designed to model the driver's intent by calculating the vehicle's front running space, collision risk and comfort loss under each scenario. And the NGSIM dataset is used to train the parameters in the GMM-HMM model and those in the revenue function. Finally, two groups of experiments are designed to compare this method with the traditional method. The experimental results show that the proposed method can predict the future behavior of traffic vehicles earlier, and can also well reflect the interaction process of vehicle behavior, and has better robustness.

INDEX TERMS Game theory, GMM-HMM, behavior prediction, traffic car, NGSIM dataset.

I. INTRODUCTION

The development of intelligent automobile technology has greatly improved traffic safety, social progress and the efficiency and quality of people's daily travel. At present, whether some advanced driving assistance systems or automatic driving systems, accurate prediction of the movement of other traffic participants in the driving environment is an indispensable and important part of the whole system. Vehicle is the main body of traffic behavior, and the motion prediction of traffic vehicle expresses the understanding of the future dynamic change of traffic environment, which is a necessary prerequisite for the behavior decision-making and trajectory planning of intelligent vehicles. In traffic vehicle motion prediction, the behavior of traffic vehicles is often abstracted out, and the behavior prediction of traffic vehicles need to be carried out first.

To predict the future behavior of traffic vehicles efficiently and accurately is the goal that many researchers chase after. The methods to predict traffic vehicle behavior can be divided into two methods: to predict traffic vehicle behavior directly through prototype trajectory and to predict traffic vehicle behavior based on vehicle interaction. The prototype trajectory method matches the vehicle's prototype trajectory with the vehicle's possible motion pattern, and then combines the matching results with the historical trajectory for behavior identification. The driver behavior can be extracted by many methods, H. Liu et al propose a defect-repairable feature extraction method based on a deep sparse autoencoder (DSAE) to extract low-dimensional time-series data that represents driving behavior [1]. And the prototype trajectory can be obtained by classifying the vehicle's sample trajectories, two kinds of Spectral clustering method are adopted by Atev et al to classify the trajectory [2], and Vasquez et al classify the trajectory by calculating the mean and standard deviation of the sample trajectory [3]. The Gaussian Mixture Model (GMM) has a good performance in the classifying trajectories [4], [5]. The matching between the observed prototype trajectory of vehicles and the movement patterns obtained by training is the key to affect the prediction effect. The usual method is to define a measure to represent the degree of fit between a trajectory and the historical trajectory,

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and Hu et al represent this measure through the Euclidean distance between trajectory points [6]. In addition, data driven methods have been well researched. L.Huang et al propose a neural-network-based operational level lane-changing model using data driven methods, for capturing drivers' lane changing behavior [7].

Behavior prediction based on interaction is the most comprehensive method. In motion prediction, it considers the main vehicle and other surrounding vehicles as interacting entities and considers the behavioral dependence between them. One way to think about interactions between traffic participants is to assume that all drivers will try to avoid collisions and choose the least risky driving behavior by hazard assessment. Lawitzky adopted this idea and first provided the prior probability distribution of the driving intention of each traffic vehicle in the motion prediction, and then made the risk assessment by considering the interaction between vehicles, and further corrected the prior distribution [8]. Another way to consider the impact of vehicle interactions is to use dynamic Bayesian networks. Agamennoni extended the dynamic Bayesian network approach to include vehicular interactions in Behavior prediction, at the same time, traffic rules were taken into account while modeling vehicle behavior [9], [10], then statistical reasoning was used to calculate the posterior probability distribution of motion states. In order to deal with the behavioral interaction between traffic vehicles, the game theory based approach has also aroused the interest of researchers. Martin used the non-cooperative game to analyze the movement of vehicles. When calculating the revenue of vehicles, he first considered the cost of the trajectory itself under various behaviors, and then calculated the final revenue by using collision detection [11]. To predict the behavior of vehicles in traffic scenarios, Oyler built a Game-theory based traffic model that could reflect the interactions of multiple drivers [12].

Through the above introduction to the research status of traffic vehicle behavior prediction methods, it can be found that at present, some scholars in the field of traffic vehicle behavior prediction have made a lot of in-depth research, but there are still the following deficiencies: (1) The behavior prediction method based on the prototype trajectory will study the traffic vehicle to be predicted as an independent individual, ignoring the influence of other surrounding vehicles on it. Although the calculation efficiency is high, it is difficult to accurately predict the vehicle behavior in the traffic environment full of interaction, and at the same time, it ignores the driving intention of the driver. (2) At present, dynamic Bayesian network is the representative method to consider the interaction between vehicles. Although this method considers the behavioral interaction between vehicles, it is expressed in the form of pure mathematics, which does not have a good interpretation. In addition, it does not specifically model the driver's intention.

Whether it is a human-driven vehicle or a vehicle with autonomous driving ability, it is an agent that will respond to the stimulation of the surrounding environment. Therefore, using game theory to analyze the behavior of traffic vehicles is a very effective method. However, at present, there is not a set of mature and perfect prediction framework for this method in motion prediction. Based on this, this paper proposes an interactive behavior prediction method based on Game theory and Markov model, which includes driver intention prediction and driver behavior recognition. In terms of driver intention prediction, the method on the basis of fully considering the interaction between vehicles, designs the revenue function to predict the expected utility of vehicles in each scenario that represents the probability of the vehicle choosing various behaviors, which better solves the problem of the prediction of driver intention prediction. In terms of behavior recognition, this paper established a GMM-HMM behavior recognition model, which can identify the driver's behavior through the vehicle's historical trajectory. Finally, two sets of experiments are designed to verify our proposed method. The main contributions of this paper are: (1) To improve the precision and robustness of vehicle behavior prediction, a method based on Game theory and HMM is proposed for vehicle behavior prediction. (2) To well design the driver's driving intent, a revenue function is designed and calibrated to model the driver's driving intent, combined with HMM to predict vehicle future behavior. (3) Useful data is filtered and extracted from the NGSIM Dataset to train the GMM-HMM model and revenue function to obtain their parameters. (4) Two sets of experiments are designed to demonstrate the feasibility of our proposed method.

The remainder of this paper is structured as follows. Section II introduces Game theory method and framework of behavior method respectively. In Section III, the GMM-HMM model is constructed and trained in order to recognize the behavior of traffic vehicles, and sliding time window method is used to extract the trajectory feature. Revenue function reflecting driving intent is designed and calibrated in Section IV. To demonstrate the advantage of this method which considers the driver's driving intent and the interaction between vehicles, two sets of experiments are designed and the experimental results are analyzed in Section V. Finally, Section VI con-cludes the paper by summarizing the findings.

II. GAME THEORY AND THE FRAMEWORK OF BEHAVIOR PREDICTION METHOD

A. INTRODUCTION TO GAME THEORY METHOD

Game Theory can be defined as the study of mathematical models expressing conflict and cooperation between intelligent and rational decision makers [13]. This method is widely used in all kinds of decision making fields. At first, it was mainly applied in economics [14], but later it was expanded in wireless sensor networks [15], biology [16], sociology and other aspects. With the development of science and technology, Game Theory has also been widely applied in computer technology, artificial intelligence, robotics, engineering manufacturing, engineering control and other fields [17]. One of the main reasons that Game Theory can be applied to so many areas is its ability to express interactions between multiple players and obtain the optimal solution to the expectation.

In the intelligent car driving scenario, the interaction between traffic participants can be abstracted as a game with multiple players, each with their own strategy profile. By solving the Equilibrium of the game, we can get the most likely behavior of the traffic vehicle. In the traffic environment, the vehicle driving behaviors can be seen as a non-cooperative game. Non-cooperative games study each player as an individual. Each player makes decisions independently and choose their strategy by maximizing revenue in the fixed scenario, regardless of other players' strategies. This revenue value may include factors such as hazard assessment, comfort index, economy and driving efficiency.

Expected utility theory, is theory about how to make the optimal decision in the case of a risk. It deals with situations where the player doesn't know how much he's going to gain from a particular decision, at this moment, the player tend to choose the action that has the highest expected utility. Expected utility can be directly defined as the sum of the product of the revenue of all possible behavior combinations and the probability of their occurrence. For a vehicle being predicted, it cannot accurately know the benefits brought by taking a certain action, so it can only calculate the expected utility brought by each behavior according to the expected utility theory, and selects the behavior with the highest utility value.

B. FRAMEWORK DESIGN OF BEHAVIOR PREDICTION METHOD

Take the traffic scene shown in Figure 1 for example, define a game of regular form $\boldsymbol{G} = (\boldsymbol{N}, \boldsymbol{A}, \boldsymbol{u})$, where $\boldsymbol{N} = (p_1, \ldots, p_i, \ldots, p_n)$ represents a (finite) set of n players, $\boldsymbol{a} = (a_1, \ldots, a_i, \ldots, a_n) \in \boldsymbol{A}$, $\boldsymbol{a}$ represents a strategy combination of n players, $\boldsymbol{u} = (u_1, \ldots, u_i, \ldots, u_n)$ here $u_i : \boldsymbol{A} \mapsto R$ is the revenue function of player i.

There are three players in the scene which represent three cars. They can be expressed as $\boldsymbol{N} = \{A, B, C\}$, their respective sets of behaviors can be defined as:

$$\begin{aligned}
\mathcal{M}_A &= \left\{m_{A,k} \mid k \in \{1,2\}\right\} = \{LCL, LK\} \\
\mathcal{M}_B &= \left\{m_{B,i} \mid i \in \{1,2\}\right\} = \{LK, LCR\} \\
\mathcal{M}_C &= \left\{m_{C,j} \mid j \in \{1,2,3\}\right\} = \{LCL, LK, LCR\} \qquad (1)
\end{aligned}$$

where, $m_{A,k}$ represents the class k behavior of the car A, LCL, LK, LCR represent Lane Change to Left, Lane Keep, Lane Change to Right respectively.

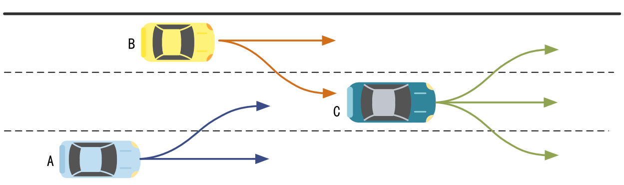

FIGURE 1. Vehicle interaction diagram.

For simplicity, we define that $|\mathcal{M}_A|$ represents the number of behaviors that the car D can take. For this game, the possible behavior combinations of the three cars can have $|\mathcal{M}_A| \times |\mathcal{M}_B| \times |\mathcal{M}_C| = 12$ categories. The revenue function of the three players gained from each combination of actions can be denoted as:

$$\begin{aligned}
&\mathcal{U}_A\left(\boldsymbol{m}_{A,k}, \boldsymbol{m}_{B,i}, \boldsymbol{m}_{C,j}\right) \\
&\mathcal{U}_B\left(\boldsymbol{m}_{A,k}, \boldsymbol{m}_{B,i}, \boldsymbol{m}_{C,j}\right) \\
&\mathcal{U}_C\left(\boldsymbol{m}_{A,k}, \boldsymbol{m}_{B,i}, \boldsymbol{m}_{C,j}\right)
\end{aligned}$$

where

$$\boldsymbol{m}_{A,k} \in \mathcal{M}_A, \boldsymbol{m}_{B,i} \in \mathcal{M}_B, \boldsymbol{m}_{C,j} \in \mathcal{M}_C \qquad (2)$$

Since the future behavior of a driver is uncertain when driving on the road, there is probability for each behavior of A, B and C, and the probability of each car choosing a certain behavior can be represented as $p\left(m_{A,k}\right), p\left(m_{B,i}\right)$ and $p\left(m_{C,j}\right)$ respectively. In this paper, it is assumed that the drivers are rational, the situation of the vehicle driving out of the road is not considered, i.e., $p\left(m_{A,LCR}\right) = p\left(m_{B,LCL}\right) = 0$.

According to the expected utility theory, when a vehicle chooses its own behavior, it chooses the behavior that produces the highest expected utility. For car A, according to the expected utility theory, the expected utility values generated by two alternative behaviors are respectively:

$$\begin{aligned}
\mathcal{U}\left(m_{A,LCL}\right) &= \sum\nolimits_{m_{B,i}\in\mathcal{M}_B} \sum\nolimits_{m_{C,j}\in\mathcal{M}_C} p\left(m_{B,i}\right) p\left(m_{C,j}\right) \\
&\quad \times u_A\left(m_{A,LCL}, m_{B,i}, m_{C,j}\right) \\
\mathcal{U}\left(m_{A,LK}\right) &= \sum\nolimits_{m_{B,i}\in\mathcal{M}_B} \sum\nolimits_{m_{C,j}\in\mathcal{M}_C} p\left(m_{B,i}\right) p\left(m_{C,j}\right) \\
&\quad \times u_A\left(m_{A,LK}, m_{B,i}, m_{C,j}\right) \qquad (3)
\end{aligned}$$

Each car in the car set $\mathcal{T}$ takes a behavior $m_{i,j}$, for convenience, here we define a concept of "scenario" to describe the behavior combination of all interested cars, which can be denoted as:

$$\mathcal{H} = \bigcup\nolimits_{\substack{t\in\mathcal{T} \\ m_{t,j}\in\mathcal{M}_t}} m_{t,j} \qquad (4)$$

Formula (3) is generalized to obtain the definition of the expected utility of a vehicle behavior. For car $\boldsymbol{\mathcal{V}_o}$ to be predicted in car set $\mathcal{T}$, the expected utility of it choosing a certain behavior $m_{o,i}$ is:

$$\begin{aligned}
&\mathcal{U}\left(m_{o,i}\right) \\
&= \sum\nolimits_{\substack{t\in\mathcal{T},t\neq o \\ m_{t,j}\in\mathcal{M}_t}} u_o\left(m_{o,i}, \bigcup\nolimits_{t\in\mathcal{T},t\neq o} m_{t,j}\right) \prod\nolimits_{t\in\mathcal{T},t\neq o} p\left(m_{t,j}\right) \qquad (5)
\end{aligned}$$

For the traffic car to be predicted, the expected utility value i.e. $\mathcal{U}\left(m_{o,i}\right)$ of it choosing a certain behavior actually represents the probability that the driver will choose such behavior $m_{o,i}$ in the future at the level of intention. Therefore, under the assumption that all drivers are rational, By normalizing the value of $\mathcal{U}\left(m_{o,i}\right)$, we can obtain the intention probability of drivers choosing a certain behavior $m_{o,i}$ in a period of time in the future:

$$p_{intend}\left(m_{o,i}\,|\,\mathcal{S}^{t-h:t}\right) = \mathcal{G}\left(\mathcal{U}\left(m_{o,i}\right)\right) \tag{6}$$

where, $\mathcal{S}^{t-h:t}$ is the movement state of other surrounding vehicles in the past (t-h) time period, $\mathcal{G}(\cdot)$ is the normalized function, which directly expresses the relationship between expected utility and intention probability and can be expressed as:

$$\mathcal{G}\left(\mathcal{U}(m_{o,i})\right) = \frac{e^{\mathcal{U}(m_{o,i})}}{\sum_{j=1}^{|M_o|} e^{\mathcal{U}}(m_{o,j})} \tag{7}$$

$p_{intend}\left(m_{o,i}\,|\,\mathcal{S}^{t-h:t}\right)$ is the judgment of the future driving intention of the vehicle to be predicted. Accurate predictions of traffic car $\mathcal{V}_o$' behavior also need to combined with the history trajectory of car $\mathcal{V}_o$, while the behavior recognition results of the vehicle i.e. $p_{recog}\left(m_{o,i}\,|\,\mathcal{S}_o^{t-h:t}\right)$ just reflects the recognition of its behavior based on the historical trajectory. Combining the future driving intention and the behavior recognition, the final behavior prediction probability can be expressed as following equation:

$$p\left(m_{o,i}\,|\,\mathcal{S}^{t-h:t}\right) = \tau_1 p_{recog}\left(m_{o,i}\,|\,\mathcal{S}_o^{t-h:t}\right) + \tau_2 p_{intend}\left(m_{o,i}\,|\,\mathcal{S}^{t-h:t}\right) \tag{8}$$

where, τ_1 and τ_2 are respectively the weight coefficients of intention probability and behavior recognition probability, which satisfy $\tau_1 + \tau_2 = 1$.

When predicting the behavior of a traffic vehicle, it is necessary to know the probabilities of various behaviors that other vehicles around will take in the future, and because the behaviors of vehicles interact with each other. When predicting the behavior of each concerned traffic vehicle, it will fall into an endless cycle. Therefore, this paper introduces the idea of level-k hierarchical reasoning [18]. In the framework of level-k, a level-0 vehicle can be defined as one that does not consider the possible future behavior of other vehicles. In addition, if a car assumes that other surrounding vehicles are level-0 vehicles, and the car makes its own decision under this assumption, then the car is defined as level-1 vehicles. By analogy, we can get the definition of level-k vehicles.

According to the idea of level-k hierarchical reasoning, the main vehicle is considered as an agent one level higher than the traffic vehicle in this paper, so the probability distribution of the behavior of other traffic vehicles in the calculation is the final behavior prediction result, i.e., $p\left(\boldsymbol{m}_t\right) = p\left(\boldsymbol{m}_t\,|\,\mathrm{S}^{t-h:t}\right)$. However, from the perspective of traffic vehicles themselves, they are not more advanced than the surrounding traffic vehicles. They can only calculate the possible behavior distribution i.e. $p\left(\boldsymbol{m}_t\right)$ of these vehicles by observing the current motion state of the surrounding vehicles. And then it's going to think about every possible "scenario", and it's going to get a revenue $u_o\left(\bigcup_{t\in\mathcal{T},m_{t,j}\in\mathcal{M}_t} m_{t,j}\right)$ in that "scenario". Combining $u_o\left(\bigcup_{t\in\mathcal{T},m_{t,j}\in\mathcal{M}_t} m_{t,j}\right)$ with $p\left(\boldsymbol{m}_t\right)$, it calculates the expected utility of each of its actions, which represents the probability of the future intentions of the vehicle $\mathcal{V}_o$. In short, the main car "assists" the car in calculating the expected utility of each of its actions, and then from this the probability distribution of the car's future intentions can be inferred.

It is worth mentioning that, although the main vehicle is clear about what behavior it is carrying out at the moment, for the traffic vehicle, it cannot accurately know the current behavior of the main vehicle, so it still needs to calculate the probability distribution of the current behavior of the main vehicle according to the motion state information of the main vehicle, which to some extent reflects the interaction process between the traffic vehicle and the main vehicle. When using the proposed method predict the behavior of traffic vehicles, the main vehicle and the surrounding traffic vehicles are considered as a whole with mutual influence, not only considering the influence of traffic vehicles on the behavior of the main vehicle, but also considering the possible reaction of traffic vehicles to the behavior of the main vehicle.

After the above discussion, it can be found that both the prediction of the traffic vehicle's behavior and the behavioral decision of the main vehicle need to estimate the current behavioral probability distribution i.e. $p\left(\boldsymbol{m}_t\right)$ of other vehicles. The revenue matrix $u\left(\bigcup_{t\in\mathcal{T},m_{t,j}\in\mathcal{M}_t} m_{t,j}\right)$ under each possible scenario is calculated. This paper studies these two parts as two separately available modules. Abstract the functions of these two modules, we can get the following definition: (1) vehicle behavior recognition module, the probability distribution of the observed vehicle is estimated by the data obtained from the on-board sensor, in this paper, a behavior recognition method based on Gaussian Mixture Hidden Markov Model (GMM-HMM) is used. (2) Specific scenario revenue calculation module, given each possible scenario, the observed vehicle's revenue is then calculated based on the defined revenue function.

III. CONSTRUCTION AND TRAIN OF GMM-HMM MODEL

In order to recognize the behavior of traffic vehicles, this paper uses a behavior recognition method based on Gaussian Mixture Hidden Markov Model (GMM-HMM). Hidden Markov Model (HMM) is a temporal sequence probability Model that uses a single discrete random variable to describe the process state. It is the Dynamic Bayesian Network (DBN) with the simplest structure [19]. Hidden Markov Model has Hidden Markov property, that is, the state of the system at any moment is only related to the state at the previous moment. Therefore, the joint probability distribution of all variables in the model can be written as:

$$p\left(q_1, \boldsymbol{O}_1, \ldots, q_T, \boldsymbol{O}_T\right) = p\left(q_1\,|\,\pi\right)\left[\prod_{i=1}^{T-1} p\left(q_{i+1}\,|\,q_i, \boldsymbol{A}\right)\right] \times \prod_{j=1}^{T} p\left(\boldsymbol{O}_j\,|\,q_j, \boldsymbol{\phi}\right) \tag{9}$$

where, q is the state variable of the model, and the corresponding state sequence is $\boldsymbol{Q} = q_1 q_2 \ldots q_T$, q_t represents the state of the system at time t, the value set of which is $\boldsymbol{S} = \{s_1, s_2, \ldots, s_N\}$. O is the observation variable and the corresponding observation sequence is $\boldsymbol{O} = \boldsymbol{O}_1 \boldsymbol{O}_2 \ldots \boldsymbol{O}_T$, where, $\boldsymbol{O}_t$ represents the value of the observed variable at time t. The observable variables can be multiple, i.e., $\boldsymbol{O}_t = \left[O_t^1, O_t^2, \ldots, O_t^G\right]$, where G represents the number of the observable variable O.

To determine the above equation, the state transition probability, the output observation probability and the initial state probability should be given. the state transition probability can be represented by probability transition matrix $\boldsymbol{A}_{N\times N}$, where it's element a_{ij} can be written as:

$$a_{ij} = p\left(q_{t+1} = s_j \mid q_t = s_i\right), \quad i,j \in [1,N], \ t \in [1,T-1] \tag{10}$$

Output observation probability refers to the probability that the system outputs observations in each state, $b_i(\boldsymbol{O}_t)$ is used to represent the probability of the value of the output observation variable O that is outputted by the system in state i at time t. As shown in the following formula, where $\boldsymbol{\phi}$ is the parameter set that controls the output observation probability distribution.

$$b_i(\boldsymbol{O}_t) = p\left(\boldsymbol{O}_t \mid q_t = s_i, \boldsymbol{\phi}\right), \quad i \in [1,N], \ t \in [1,T] \tag{11}$$

Initial state probability refers to the probability that the system is in each state at the initial moment, it can be written as $\boldsymbol{\pi} = (\pi_1, \pi_2, \ldots, \pi_N)$, where:

$$\pi_i = p(q_1 = s_i), \quad i \in [1,N] \tag{12}$$

In the process of traffic vehicle behavior identification, the vehicle motion state obtained through sensors is a continuous variable. Therefore, CHMM is used in this paper. The output observation probability of CHMM is expressed as a continuous probability distribution. Theoretically, the Gaussian Mixture Model (GMM) can be used to represent any form of continuous probability distribution, and it has some other good computational characteristics. Therefore, it is most commonly used to represent the output observation probability. The HMM that uses GMM to represent the output observation probability is written as GMM-HMM, and its output observation probability is:

$$b_i(\boldsymbol{O}) = \sum\nolimits_{m=1}^{M} c_{im} \mathcal{N}\left(\boldsymbol{O} \mid \boldsymbol{\mu_{im}}, \boldsymbol{\Sigma_{im}}\right), \quad i \in [1,N] \tag{13}$$

where, $\boldsymbol{\phi} = \{\boldsymbol{c}, \boldsymbol{\mu}, \boldsymbol{\Sigma}\}$ is used to represent the parameters of the output probability, c_{im} is the weight coefficient of the m'th Gaussian distribution in the state of i, M is the number of Gaussian distribution in GMM, c_{im} satisfies:

$$\sum\nolimits_{m=1}^{M} c_{im} = 1\ 0 \leq_{im} \leq 0, \quad i \in [1,N], \ m \in [1,M] \tag{14}$$

$\boldsymbol{\mu_{im}} \in \mathbb{R}^{G\times 1}$ and $\boldsymbol{\Sigma_{im}} \in \mathbb{R}^{G\times G}$ are $G \times 1$ dimensional mean vector and $G \times G$ dimensional covariance matrix of Gaussian distribution $\mathcal{N}\left(\boldsymbol{O} \mid \boldsymbol{\mu_{im}}, \boldsymbol{\Sigma_{im}}\right)$, respectively. The probability density function of Gaussian distribution is:

$$\mathcal{N}\left(\boldsymbol{O} \mid \boldsymbol{\mu}_{im}, \boldsymbol{\Sigma}_{im}\right) = \frac{1}{(2\pi)^{G/2}} \frac{1}{|\boldsymbol{\Sigma}_{im}|^{1/2}} \exp\left\{-\frac{1}{2}\left(\boldsymbol{O} - \boldsymbol{\mu}_{im}\right)^T \boldsymbol{\Sigma}_{im}^{-1} \left(\boldsymbol{O} - \boldsymbol{\mu}_{im}\right)\right\} \tag{15}$$

According to the above introduction to GMM-HMM, we can use $\boldsymbol{\lambda} = \{\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{\phi}\}$ represents the parameter of GMM-HMM.

This paper focuses on the study of the vehicle's lateral behavior, and takes the three lateral behaviors of the vehicle as the possible states of hidden variables in the GMM-HMM model i.e., $\boldsymbol{S} = \{s_1, s_2, s_3\} = \{LCL, LK, LCR\}$. This paper selects lateral deviation d and lateral deviation velocity $\dot{d}$ as observation variables:

$$\boldsymbol{O} = \left[d, \dot{d}\right] \tag{16}$$

According to the selected hidden state and observed variables, GMM-HMM schematic diagram of behavior recognition can be drawn (as shown in Figure 2), As you can see from the figure, the vehicle' behavior can remain unchanged (a_{ii}), can also be switched to other behaviors ($a_{ij}, i \neq j$), the transition probability of LCL, LK and LCR is:

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{a_{11}} & \boldsymbol{a_{12}} & \boldsymbol{a_{13}} \\ \boldsymbol{a_{21}} & \boldsymbol{a_{22}} & \boldsymbol{a_{23}} \\ \boldsymbol{a_{31}} & \boldsymbol{a_{32}} & \boldsymbol{a_{33}} \end{bmatrix} \tag{17}$$

The behavior of the vehicle will be estimated by observation variable $\boldsymbol{O} = \left[d, \dot{d}\right]$, the probability distribution of observed variable complying with behavior i is:

$$b_i(\boldsymbol{O}) = \sum\nolimits_{m=1}^{M} c_{im} \mathcal{N}\left(\boldsymbol{O} \mid \boldsymbol{\mu}_{im}, \boldsymbol{\Sigma}_{im}\right), \quad i \in [1, 3] \tag{18}$$

where $\mathcal{N}\left(\boldsymbol{O} \mid \boldsymbol{\mu}_{im}, \boldsymbol{\Sigma}_{im}\right)$ is a 2-dimensional single Gaussian distribution.

The behavior of the vehicle is continuous, and it is not enough to identify the behavior of the vehicle only with the data of the observed variable at one time. Therefore, this paper adopts the method of sliding time window to obtain the trajectory characteristics of vehicles.

As shown in figure 3, when behavior identification is carried out at time t, n feature points on the trajectory are sampled by time interval Δt_c and taken as the input of the

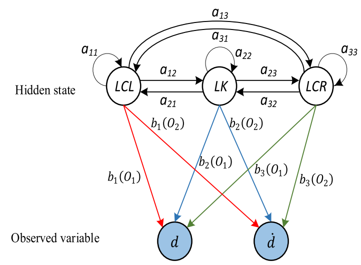

FIGURE 2. GMM-HMM for behavior recognition.

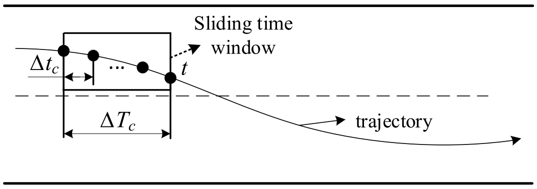

FIGURE 3. Trajectory feature extraction using sliding time window method.

estimation algorithm, therefore, the time width of the time window is:

$$\Delta T_c = n \cdot \Delta t_c \tag{19}$$

The value of the observed variable at time t can be obtained from sampled n feature points:

$$\boldsymbol{O}_t = \left[\boldsymbol{d}_t, \dot{\boldsymbol{d}}_t\right] \in \mathbb{R}^{n\times 2} \tag{20}$$

where d and $\dot{d}$ are $n \times 1$ dimensional vector:

$$\begin{aligned}\boldsymbol{d}_t &= \left[d\left(t-(n-1)\Delta t_c\right), d\left(t-(n-2)\Delta t_c\right), \ldots, d\left(t\right)\right]^T \in \mathbb{R}^n\\ \dot{\boldsymbol{d}}_t &= \left[\dot{d}\left(t-(n-1)\Delta t_c\right), \dot{d}\left(t-(n-2)\Delta t_c\right), \ldots, \dot{d}\left(t\right)\right]^T \in \mathbb{R}^n\end{aligned} \tag{21}$$

So far, we obtained the observation data at n feature points by sliding time window, for simplicity, the obtained observation sequence is denoted as $\boldsymbol{O} = \boldsymbol{O_1 O_2 \ldots O_T}$. Calculate the probability distribution of vehicle state at every time t:

$$\gamma_t(i) = p\left(q_t = s_i \mid \boldsymbol{O}, \boldsymbol{\lambda}\right), \quad i \in [1, N], \ t \in [1, T] \tag{22}$$

Further, the above equation can be converted into:

$$\gamma_t(i) = \frac{\alpha_t(i)\,\beta_t(i)}{\sum_{j=1}^{N} \alpha_t(j)\,\beta_t(j)} \tag{23}$$

where, forward variable $\alpha_t(i)$ and backward variable $\beta_t(i)$ are respectively defined as:

$$\begin{aligned}\alpha_t(i) &= p\left(\boldsymbol{O}_1\boldsymbol{O}_2\ldots\boldsymbol{O}_t, q_t = s_i \mid \boldsymbol{\lambda}\right)\\ \beta_t(i) &= p\left(\boldsymbol{O}_{t+1}\boldsymbol{O}_{t+2}\ldots\boldsymbol{O}_T \mid q_t = s_i, \boldsymbol{\lambda}\right)\end{aligned} \tag{24}$$

For a given observation sequence $\boldsymbol{O} = \boldsymbol{O_1 O_2 \ldots O_T}$, the parameter $\boldsymbol{\lambda} = \{\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{\phi}\}$ of GMM-HMM can be determined by Maximum Likelihood method. The Expectation Maximization (EM) is used to maximize the Maximum Likelihood function, and further to estimate the model parameter i.e. $\boldsymbol{\lambda}$. The EM algorithm first selects a set of initial parameters for the model, denoted as $\bar{\boldsymbol{\lambda}}$. The estimation for $\boldsymbol{\lambda} = \{\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{\phi}\}$ is:

$$\bar{\pi}_i = \frac{\gamma_1(i)}{\sum_{j=1}^{N} \gamma_1(j)} \tag{25}$$

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{n=1}^{N}\sum_{t=1}^{T-1} \xi_t(i,n)} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{26}$$

where $\xi_t(i,j)$ represents the joint posterior probability distribution between two consecutive hidden variables, $\gamma_t(i)$ has been defined in (23), but the $\boldsymbol{\lambda}$ is substituted by $\bar{\boldsymbol{\lambda}}$. The expression for $\xi_t(i,j)$ is:

$$\begin{aligned}\xi_t(i,j) &= p\left(q_t = s_i, q_{t+1} = s_j \mid \boldsymbol{O}, \bar{\boldsymbol{\lambda}}\right)\\ &= \frac{\alpha_t(i)\, b_j(\boldsymbol{O}_{t+1})\,\beta_{t+1}(j)\, a_{ij}}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i)\, b_j(\boldsymbol{O}_{t+1})\,\beta_{t+1}(j)\, a_{ij}}\end{aligned} \tag{27}$$

When the parameter $\boldsymbol{\phi} = \{\boldsymbol{c}, \boldsymbol{\mu}, \boldsymbol{\Sigma}\}$ of the output observation probability is maximized, the parameters of the output observation probability can be maximized independently for each state of the model:

$$p(\boldsymbol{O} \mid \phi_i) = b_i(\boldsymbol{O}) = \sum_{m=1}^{M} c_{im}\mathcal{N}(\boldsymbol{O} \mid \boldsymbol{\mu_{im}}, \boldsymbol{\Sigma_{im}}), \quad i \in [1, N] \tag{28}$$

For the Mixture Gaussian Model, the estimation expression of parameters can be given directly:

$$\bar{c}_{im} = \frac{\sum_{t=1}^{T} \gamma_t(i,m)}{\sum_{t=1}^{T}\sum_{m=1}^{M} \gamma_t(i,m)} \tag{29}$$

$$\bar{\boldsymbol{\mu}}_{im} = \frac{\sum_{t=1}^{T} \gamma_t(i,m)\,\boldsymbol{O}_t}{\sum_{t=1}^{T}\sum_{m=1}^{M} \gamma_t(i,m)} \tag{30}$$

$$\bar{\boldsymbol{\Sigma}}_{im} = \frac{\sum_{t=1}^{T} \gamma_t(i,m)\left(\boldsymbol{O}_t - \boldsymbol{\mu_{im}}\right)\left(\boldsymbol{O}_t - \boldsymbol{\mu_{im}}\right)^T}{\sum_{t=1}^{T} \gamma_t(i,m)} \tag{31}$$

where, $\gamma_t(i,m)$ represents the probability of the m'th Gaussian distribution in the observation probability outputted by the system in the state i at time t, and its expression is as follows:

$$\gamma_t(i,m) = \left[\frac{\alpha_t(i)\,\beta_t(i)}{\sum_{i=1}^{N} \alpha_t(i)\,\beta_t(i)}\right]\left[\frac{c_{im}\mathcal{N}\left(\boldsymbol{O}_t \mid \boldsymbol{\mu_{im}}, \boldsymbol{\Sigma_{im}}\right)}{\sum_{m=1}^{M} c_{im}\mathcal{N}\left(\boldsymbol{O}_t \mid \boldsymbol{\mu_{im}}, \boldsymbol{\Sigma_{im}}\right)}\right] \tag{32}$$

A. MODEL TRAINING

In this paper, data of I-80 section in NGSIM [20] dataset is selected for training the model. The data set, derived from the Next Generation Simulation (NGSIM) initiative of the U.S. federal highway administration, was sampled at a frequency of 10Hz and recorded information including vehicle coordinates, speed, acceleration, vehicle type, and vehicle number. The study section is shown in Figure 4. Due to some errors and noise exist in the original data, especially the speed signal jitter is obvious, so the symmetric exponential moving average filter [21] is used in this paper to preprocess the data of vehicle coordinates, speed, and acceleration.

In this paper, trajectory samples of left lane change, lane keep and right lane change were extracted from the NGSIM traffic data set. The number of samples is shown in table 1.

TABLE 1. Parameters of training samples.

	Lane Change to Left	Lane Keeping	Lane Change to Right
Number of samples	140	150	122

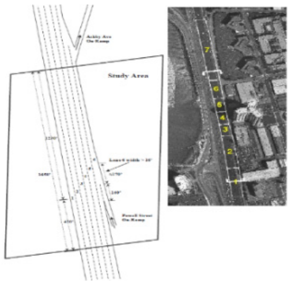

FIGURE 4. Schematic diagram of i-80 road section.

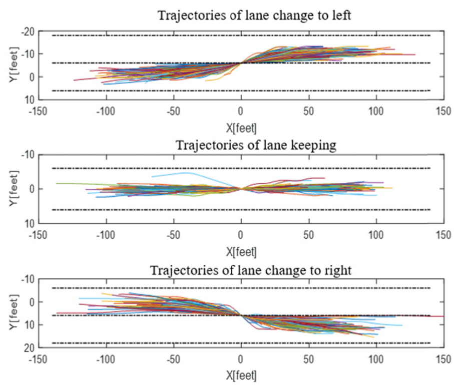

FIGURE 5. Trajectories of training samples.

The training sample trajectories are shown in Figure 5. For convenience, the intersection of lane change trajectory and lane line is taken as the reference point when extracting data, so all the sample trajectories will intersect at the reference point, However, this does not affect the training of the model, because for the behavior recognition model, this paper focuses on the lateral characteristics of the vehicle.

The NGSIM data only has the vehicle speed, but not the detailed longitudinal and lateral vehicle speed. Therefore, in this paper, the lateral deviation $\boldsymbol{d}$ is calculated by the distance between the lateral coordinate of the vehicle and the lane centerline, then the lateral deviation velocity $\dot{d}$ is obtained by calculating the gradient of $\boldsymbol{d}$. Finally, 412 observation sequences $\boldsymbol{O} = \left[\boldsymbol{d}, \dot{d}\right] \in \mathbb{R}^{50\times 2}$ were obtained, where, 50 is the length of a set of observation sequences.

When training the model, parameters need to be initialized. In general, the initial values of $\boldsymbol{\pi}$ and $\boldsymbol{A}$ have little influence on the model and can be set by means of mean value method. The behavior of the vehicle in the actual driving process generally does not switch between 1 and 3, therefore, the initial values of a_{13} and a_{31} in the state transition matrix A are set as 0, and the remaining values are uniformly distributed:

$$\hat{\pi} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \tag{33}$$

$$\hat{A} = \begin{bmatrix} \frac{1}{7} & \frac{1}{7} & 0 \\ \frac{1}{7} & \frac{1}{7} & \frac{1}{7} \\ 0 & \frac{1}{7} & \frac{1}{7} \end{bmatrix} \tag{34}$$

In this paper, GMM is used to fit the probability distribution of output variables in each hidden state, according to the characteristics of the training data and the actual recognition effect, the Gaussian distribution number of GMM is set as $M = 1$. Other parameters in ϕ are set randomly in the case that the constraint is satisfied.

IV. REVENUE FUNCTION DESIGN AND CALIBRATION

In this paper, the intention of the driver is modeled by designing the revenue function, which is based on the assumption that the behavioral decisions of the normal rational driver while driving can be abstracted into a process of constantly pursuing the revenue maximization [22].

This revenue includes both positive and negative revenue. Positive revenue includes more vehicle's front drivable space [23] and achieving the expected speed of the vehicle [24] etc. Negative revenue includes the danger brought by a certain action, the loss of comfort and so on [25], [26]. Clearly, the revenue of each driver is heavily influenced by other vehicles around them apart from their own behaviors. So, the revenue function of each car represents the interaction between cars. The following is to design the revenue function from three aspects of the vehicle's front drivable space, risk assessment and comfort.

For a given scenario H, the revenue function reflecting the driver's driving intention is defined as:

$$u(\mathcal{H}) = \omega_1 \mathscr{f} + \omega_2 \mathscr{h} + \omega_3 \mathrm{c} \tag{35}$$

where, $\mathscr{f}$, $\mathscr{h}$ and c respectively represent the vehicle's front drivable space, collision risk index and comfort index. Obviously, more vehicle's front drivable space bring positive revenue to the driver, while collision risk and the loss of comfort will bring the driver negative revenue. So in this paper $\mathscr{f}$ is defined as positive revenue, while, $\mathscr{h}$ and c are defined as negative revenue.

A. THE VEHICLE'S FRONT DRIVABLE SPACE

To determine $\mathscr{f}$, we can assume that every driver wants more space in front of the vehicle as it moves [25]. Therefore, in this paper, the available free distance in front of the vehicle is taken as a measure to represent the driver's desire to obtain more driving space:

$$\mathscr{f} = \begin{cases} \min(D_r, D_v), & \text{If there's an obstacle ahead} \\ D_v, & \text{If there are no obstacles ahead} \end{cases} \tag{36}$$

where, D_r represents the distance between the car to be observed and the front car (as shown in Figure 6, D_v is the quantity related to the visual distance.

The visual range that can be observed by drivers is limited. For various traffic signs, the visual range of young drivers is about 70m-200m, while that of older drivers is even smaller [27]. Drivers' visual range often varies, and many studies have shown that this varies with alertness, age, and fatigue [28]. Based on previous studies, here set $D_v = 150m$.

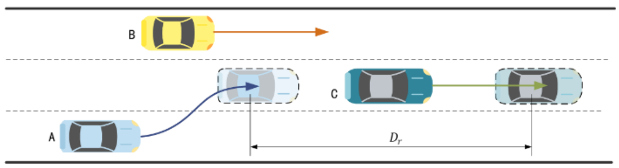

FIGURE 6. Schematic diagram of D_r.

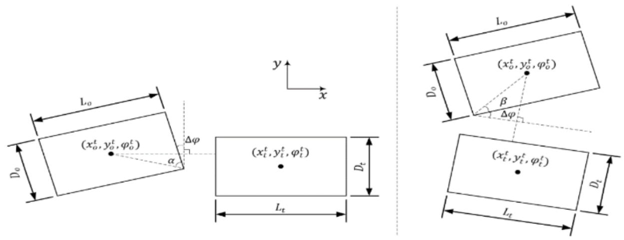

FIGURE 7. Schematic diagram of collision safety condition.

B. COLLISION RISK INDE

In the case of the given possible scenario $\mathcal{H}$, In order to improve efficiency, this paper simplifies the problem of risk assessment. Referencing [29]–[32], we firstly make a deterministic prediction of the future trajectory of each vehicle, and then carry out a risk assessment.

Assume that the length and width of the vehicle to be observed $\mathcal{V}_o$ and the surrounding vehicle $\mathcal{V}_t$ are L_o, D_o, L_t, D_t respectively, as shown in Figure 7, the coordinates and heading angle of the two cars at some certain time t are $(x_o^t, y_o^t, \varphi_o^t)$ and $(x_t^t, y_t^t, \varphi_t^t)$, deviation between the two heading angles is $\Delta\varphi = \varphi_o^t - \varphi_t^t$, The condition that there is no collision between two vehicles is that the following equation is true at any time t in the forecast cycle:

$$\left|\left(x_o^t - x_t^t\right)\cos\varphi_t^t + \left(y_o^t - y_t^t\right)\sin\varphi_t^t\right| \geq \frac{\sqrt{L_o^2 + D_o^2}}{2}\sin\left(\alpha + |\Delta\varphi|\right) + \frac{L_t}{2} + \Delta S$$

and

$$\left|\left(y_o^t - y_t^t\right)\cos\varphi_t^t - \left(x_o^t - x_t^t\right)\sin\varphi_t^t\right| \geq \frac{\sqrt{L_o^2 + D_o^2}}{2}\sin\left(\beta + |\Delta\varphi|\right) + \frac{D_t}{2} + \Delta W \tag{37}$$

where, ΔS and ΔW respectively are longitudinal and lateral safety distance. ΔS is related to Δv i.e. the relative speed between the two vehicles, Assume $\Delta S = 2\Delta v$; $\Delta W = 0.3$m:

Based on the above collision safety condition, the collision risk index in this paper is defined as follows:

$$\hbar_{ot} = \begin{cases} 0, & \text{satisfiy safety condition} \\ -\dfrac{1}{d_{ot}^{min}}, & \text{not satisfy safety condition} \end{cases} \tag{38}$$

where, d_{ot}^{min} represents the nearest distance between the vehicle to be observed $\mathcal{V}_t$ and the surrounding car $\mathcal{V}_o$ in the predict cycle.

Therefore, for the vehicle to be observed, the collision risk index between it with all its surrounding cars is:

$$\hbar = \sum\nolimits_{t\in\mathcal{T}, t\neq o} \hbar_{ot} \tag{39}$$

C. RIDE COMFORT INDEX

The acceleration of the vehicle is the most direct factor that affects the ride comfort. Generally, drivers expect to drive at a fixed speed on the road. For a given scenario H, the ride comfort index in this paper is defined as:

$$\mathrm{c} = -\int_0^T a_x^2(t) + a_y^2(t)\, dt \tag{40}$$

a_x and a_y in the above equation are the longitudinal and lateral acceleration of the vehicle to be predicted. For convenience of understanding, the expected utility of behavior $m_{o,i}$ of vehicle $\mathcal{V}_o$ is denoted as a more general form: $\mathcal{U}\left(\mathcal{S}^{t-h:t}, \boldsymbol{\theta}, m_{o,i}\right)$. Inspired by Bajari's method of identifying and estimating the revenue function in a complete information game [33], this paper proposes a method of first constructing a probability distribution function and then using maximum likelihood estimation to identify parameters. For given $\mathcal{S}^{t-h:t}$ and $\boldsymbol{\theta}$, according to equation (7), the intent probability can be further written as:

$$p_{intend}\left(m_{o,i} \,|\, \mathcal{S}^{t-h:t}, \boldsymbol{\theta}\right) = \frac{e^{\mathcal{U}\left(\mathcal{S}^{t-h:t}, \boldsymbol{\theta}, m_{o,i}\right)}}{\sum_{j=1}^{|\mathcal{M}_o|} e^{\mathcal{U}\left(\mathcal{S}^{t-h:t}, \boldsymbol{\theta}, m_{o,j}\right)}} \tag{41}$$

The above equation satisfies:

$$\sum\nolimits_{j=1}^{|\mathcal{M}_o|} p_{intend}\left(m_{o,i} \,|\, \mathcal{S}^{t-h:tn}, \boldsymbol{\theta}\right) = 1 \tag{42}$$

Assume we have a sample set $\boldsymbol{E} = \{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_N\}$, the information contained in each sample is $\boldsymbol{e} = \left(\mathcal{S}^{t-h:tn}, \boldsymbol{a}\right)$, where $\boldsymbol{a} = \left(m_{1,i}, m_{2,j}, \ldots, m_{n,k}\right)$ is the behavior combination for every vehicle. So the likelihood function can be written as:

$$L(\boldsymbol{\theta}) = \prod\nolimits_{o=1}^{N} p_{intend}\left(m_{o,i} \,|\, \mathcal{S}^{t-h:t}, \boldsymbol{\theta}\right) \tag{43}$$

Assume the estimated value of $\boldsymbol{\theta}$ is $\hat{\boldsymbol{\theta}}$, so $\hat{\boldsymbol{\theta}}$ can be obtained by the maximum likelihood method:

$$\hat{\boldsymbol{\theta}} = arg\max L(\boldsymbol{\theta}) \tag{44}$$

Likelihood function $L(\boldsymbol{\theta})$ is a multivariate nonlinear equation about parameter $\boldsymbol{\theta} = \{\omega_1, \omega_2, \omega_3\}$. The value of $\hat{\boldsymbol{\theta}}$ can be estimated by conjugate gradient methods. The final training results based on NGSIM traffic data are shown in table2.

TABLE 2. The training result of revenue function parameters.

ω_1	ω_2	ω_3
0.0532	6.0124	0.5028

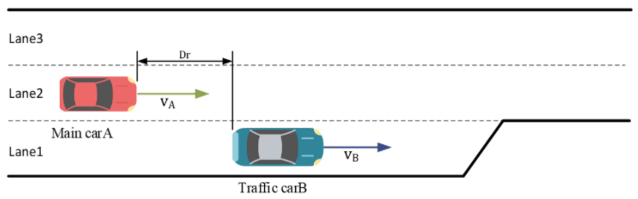

FIGURE 8. Schematic diagram of road merging simulation scenario.

V. DESIGN AND VERIFICATION OF EXPERIMENTS

In order to verify the validity of the behavior prediction method proposed in this paper, two typical traffic scenarios are designed and validated in the virtual simulation software PanoSim ® and Simulink.

The designed simulation scenario is shown in the Figure 8. The road is a straight road with three lanes, in which the rear section of Lane1 merges into Lane2. Main vehicle A is located in the middle lane Lane2, and traffic vehicle B is located in the lane Lane1. Lane 3 and lane 2 are regarded as infinite and without other traffic cars ahead. The longitudinal distance between the two vehicles is Dr, the speeds of the two cars are v_A and v_B respectively. In this scenario, if the distance between the vehicles is close and $v_A > v_B$, then the interaction between vehicle A and vehicle B will inevitably occur, so this scenario can be used to verify the proposed method.

A. EXPERIMENT I

In order to verify the advantages of the proposed behavior prediction method which considers the driver's intention through game theory compared with the traditional method based only on the vehicle's historical trajectory, a simple scenario is designed: suppose car A slows down from 56km/h to the same speed as car B and keeps going straight. At this point, from the perspective of main vehicle A, we mainly focus on the behavior prediction results of traffic vehicle B. Some information about the experiment is shown in Table 3.

The trajectories and speeds of main vehicle A and traffic vehicle B obtained through this experiment are shown in Figure 9 (a) and (b). The red and blue curves in figure (a) are the movement trajectories of traffic vehicle and main vehicle respectively. In order to express the time information in the figure, the vehicle positions at 10 discrete moments within 1∼10s are drawn. From the trajectory of the vehicle, it can be seen that the main vehicle keeps going straight, while the traffic vehicle starts to change lanes to the left around 5s, since the road ahead converges.

From figure (b), the speed changes of the two cars can be seen. After the deceleration, the main car A reaches the same speed as the traffic car b. The traffic car's speed remains at 54km/h. The slight fluctuation of the speed at 1s is caused by the driver model in Panosim® software, but the simulation effect is not affected. According to the trajectory information expressed in Figure 9, it can be seen that during the whole simulation time, the two vehicles keeps a relatively safe distance, so when the traffic vehicle wants to change lane, it will not give much consideration to the collision safety problem caused by the rear main vehicle A, which is also reflected in the traffic vehicle behavior revenue to be introduced below.

Figure 10 and Figure 11 show the revenues and expected utilities of traffic vehicle B's two behaviors of lane change to the left and lane keeping (without considering the behavior of lane change to the right) in the simulation time. It can

TABLE 3. Related information of experiment I.

Configuration	Main car A slows down and stays straight behind traffic car B at the same speed		
The initial distance between the two cars	$Dr = 30$m	Target speeds of the two cars	$v_A = v_B = 54km/h$
Lane width	12feet=3.66m	coefficient of road adhesion	0.85
Vehicle dimensions	width=1.72m, length=4.605m	Initial positions of vehicles	$(x_A, y_A) = (0,5.486)$ $(x_B, y_B) = (30,1.829)$
Total simulation time	10s	simulation step size	0.001s
Behavior recognition window width	1s	Collision detection trajectory prediction time	5s

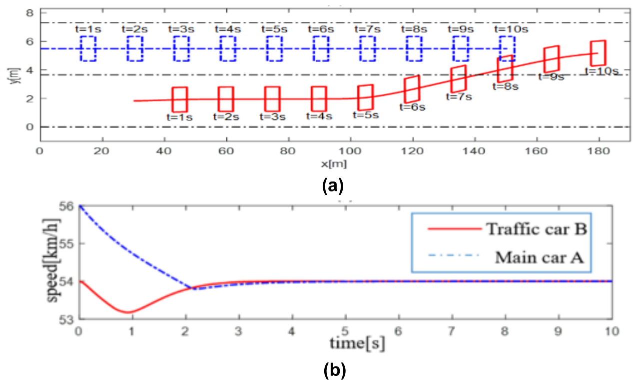

FIGURE 9. Trajectories and speeds of main vehicle and traffic vehicle (experiment I).

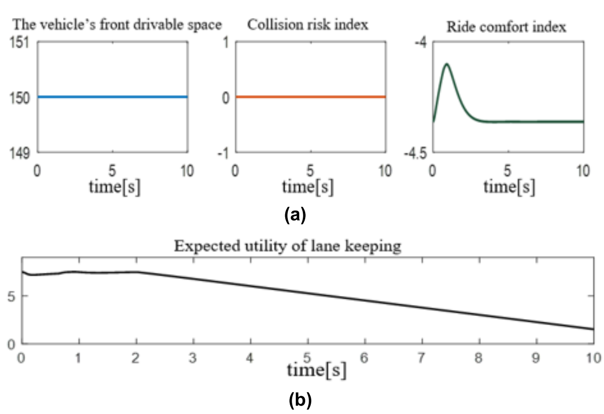

FIGURE 10. Revenue and expected utility of traffic car B changing to the left.

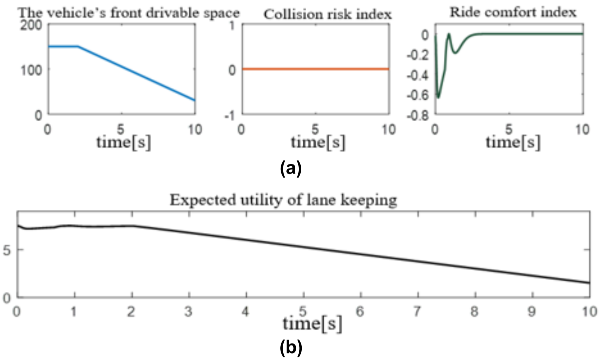

FIGURE 11. Revenue and expected utility of traffic car B keeping lane.

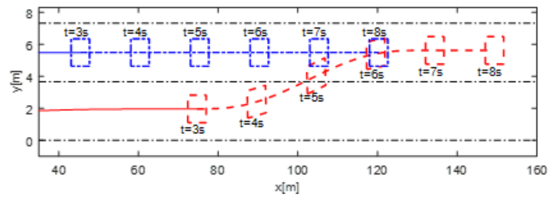

FIGURE 12. The deterministic trajectory prediction results of the two cars in the future 5s.

be seen that there is no other vehicle ahead of Lane2, so the revenue of the vehicle's front drivable space brought by the behavior of lane change to left is always $D_v = 150$, while the revenue of the vehicle's front drivable space brought by the behavior of lane keeping gradually decrease after 2s. When calculating the collision risk index, firstly, the future trajectory of the two cars is predicted with certainty. Take the deterministic trajectory prediction at 3s for example. Figure 12 shows the determ-inistic trajectory prediction results of the two cars in the future 5s, it is obvious that at all times the two cars meet the collision safety condition. This is also true at other times in the simulation, so the collision risk index of the traffic vehicle in figure 10 and figure 11 is always 0. Due to the fluctuation of the vehicle speed around the simulation time 1s, the comfort index of the vehicle also fluctuates correspondingly. The difference is that the longitudinal and lateral acceleration of the vehicle under lane keeping behavior is basically 0, so the comfort index is also close to 0, while the vehicle under left lane changing behavior will produce significant lateral acceleration, so there is a negative value in the comfort index part of the revenue function.

Since the main car A keeps going straight, the probability of going straight calculated by its behavior recognition module is always 1. From the expected utility change curves in Figure 10 and Figure 11, it can be found that the expected utility of the left lane change remains around 5.3 after the fluctuation. This shows that the space in front of the vehicle that can be brought by the left lane change has been encouraging the drivers to change lane, but because the vehicle is still far from the road junction in the early time, so the lane keeping can bring more revenue. However, after 2s, as the vehicle gets closer and closer to the junction

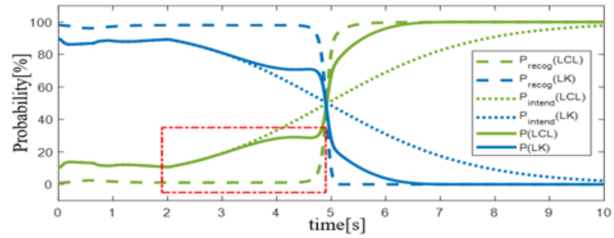

FIGURE 13. Schematic diagram of behavior prediction results (Experiment I).

of the road, the expected utility of lane keeping behavior decreases gradually.

The intention probability and behavior recognition results of the traffic vehicle are shown in Figure 13. It can be seen that the lane keeping intention probability i.e. p_{intend} (LK) obtained by the expected utility normalization starts to decline gradually after 2s, and the corresponding left lane changing intention probability i.e. p_{intend} (LCL) keeps rising, which well reflects the driver's intension change as the vehicle approaches the junction. The change of traffic vehicle behavior recognition probability fully reflects the effectiveness of the GMM-HMM based behavior recognition method proposed in this paper. At the end of 4s, when the vehicle starts to change lane, the algorithm can detect it in a very timely and effective manner, behavior recognition probability i.e. p_{recog} (LCL) of lane change to left fast rises to 100%.

The comparison between the final behavior prediction results and behavior recognition results of traffic vehicles shows the advantages of the game theory-based behavior prediction method proposed in this paper. Since any behavior of a vehicle is a continuous process, most current behavior prediction methods identify the current behavior of the vehicle through the historical trajectory of the vehicle, and then directly take the behavior recognition result as the future behavior prediction result. Essentially, this method is based on historical information to predict the future behavior of vehicles. Its main defect is that it ignores the interaction between vehicles and the surrounding environment in the future and cannot actively ''think'' about the impact of changes in the surrounding environment on the future behavior of vehicles. Therefore, it can be seen from figure 13 that the lane change probability starts to rise rapidly only when the vehicle has already made lane change.

The advantage of the proposed behavior prediction method is shown in experiment 1: when the traffic vehicle approaches the junction point of the road, even if the vehicle has not yet changed lanes, the algorithm can detect in advance that the vehicle is likely to change lane to the left (Because the traffic car also does not slow down, which means the traffic car wants to change lane in front of the main car), the corresponding lane change probability starts to increase 2∼3s earlier than the behavior recognition probability (See the red box in Figure 13). After the vehicle has changed lanes, the behavior prediction probability increases rapidly with the behavior recognition probability.

TABLE 4. Related information of experiment II.

Configuration	Main car A approaches traffic car B at a higher speed and makes decisions on its own		
The initial distance between the two cars	$Dr = 60$m	Target speeds of the two cars	$v_A = 72$km/h $v_B = 54$km/h
Lane width	12feet=3.66m	coefficient of road adhesion	0.85
Vehicle dimensions	width=1.72m, length=4.605m	Initial positions of vehicles	$(x_A, y_A) = (0,5.486)$ $(x_B, y_B) = (60,1.829)$
Total simulation time	15s	simulation step size	0.001s
Behavior recognition window width	1s	Collision detection trajectory prediction time	5s

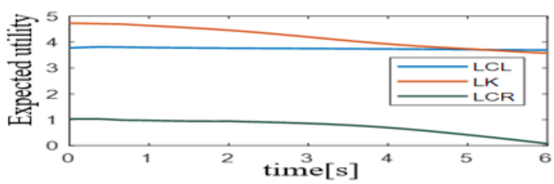

FIGURE 14. The expected utilities of the main vehicle taking different behaviors.

B. EXPERIMENT II

Another core content of interactive behavior prediction method is to consider the interaction between vehicle behaviors when conducting the behavior prediction. Therefore, experiment II is designed in this paper for verification. Experiment II assumes that main car A approaches traffic car B at a higher speed of 72km/h, and makes decisions on its own. The relevant information of the experiment is shown in table 4.

Figure 14 is the expected utility of the three behaviors of the main vehicle. The expected utility is related to the predicted results of the traffic vehicle behavior and the revenue under each scenario. The main vehicle keeps going straight on Lane2 at first, and the predicted probability of the left lane change of the traffic vehicle will start to increase as the traffic vehicle keeps approaching the road junction. As the speed of the main vehicle is higher than that of the traffic vehicle, the distance between the two vehicles will decrease, and the collision risk caused by the traffic vehicle's left lane change will also increase. In addition, under the situation that the main vehicle keeps going straight and the traffic vehicle changes lanes to the left, the revenue of the vehicle's front drivable space will decrease. The result of these two points is that the expected utility of lane keeping behavior of the main vehicle will gradually decline. Around 5s, the expected utility of lane keeping of the main vehicle is lower than the expected utility of lane change to the left. At this point, the main vehicle will make a decision to perform behavior of lane change to the left.

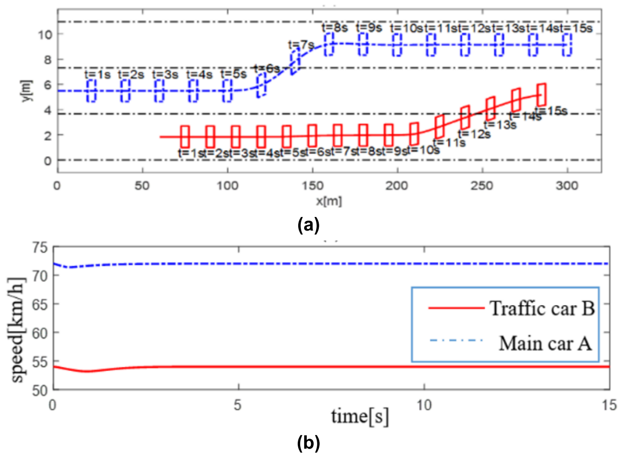

FIGURE 15. Trajectories and speeds of main vehicle and traffic vehicle (experiment II).

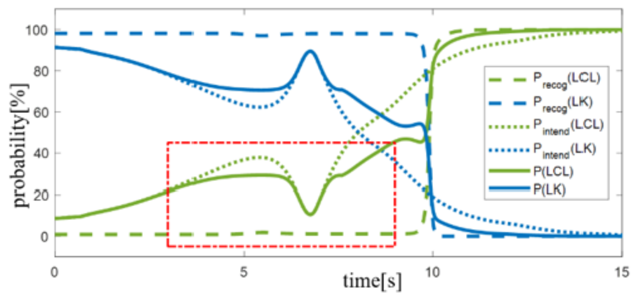

FIGURE 16. Schematic diagram of behavior prediction results (Experiment II).

The final trajectories and speeds of the two cars are shown in Figure 15. From Figure 15 (a), it can be clearly seen that the main car made a left lane change at 5s in order to leave a safe lane change area for the traffic vehicle and avoid the speed loss caused by the left lane change of the traffic vehicles ahead.

The intention probability, behavior recognition probability and the final behavior prediction result of experiment II are shown in Figure 16. Since the movement trajectory of the traffic vehicle is basically the same as that of experiment 1, the behavior recognition probability is also consistent with experiment I, when the vehicle changes lanes, the lane change to left probability quickly rises to 1, while the lane keeping probability drops to 0. The difference is the intention probability of the traffic vehicle. It's can be seen that the intention probability of the left lane change i.e. p_{intend} (LCL) is the same as experiment 1 at the beginning, it also increases gradually as the vehicle approaches the intersection point, however, at around 4s, the collision risk of the lane change to the left increases due to the continuous approach of the rear main vehicle, so the intention probability of lane change to the left starts to stop going up (as shown in red box), and turn to decline as the distance between the two cars further decrease. By the time the main vehicle has completed the lane change to the left, the risk of collision is eliminated and the traffic car's intention probability of lane change to the left is gradually rising again. The final predicted probability of the traffic vehicle's lane change to the left before the it changes to left lane is approximately the same as $p_{intend}(LCL)$, and then rises to 1 when the traffic vehicle starts to change lanes. Since the right lane change behavior of traffic vehicles is not considered, so, $p(LCL) + p(LK) = 1$, the change of lane keeping behavior prediction results is just the opposite of that of the left lane change behavior.

From the changes of the above behavior prediction results, compared with the traditional methods (i.e. the behavior recognition results are treated as the behavior prediction results), the behavior prediction results proposed in this paper will change in real time with the changes of the surrounding environment. As shown in Figure 16, as the main vehicle approaches the traffic vehicle from behind and then changes lanes to the left, the predicted results of the traffic vehicle's behavior will also change, while the predicted results of the traditional method are only related to the predicted movement state of the vehicle itself. This reflects the mutual influence and interaction between vehicles. When the main vehicle conducts the behavior prediction of the surrounding traffic vehicles, the behavior prediction results of the traffic vehicles are not only related to its own motion state, but also influenced by the behavior of the main vehicle.

From the above discussion, it can be found that compared with the traditional method of behavior prediction (i.e. $p_{recog}(LCL/LK)$), the method described in this paper is able to show the reaction of vehicles to possible dangerous situations by considering the interaction of the behaviors between vehicles. Therefore, the final behavior prediction results are more robust and it will not produce wrong prediction results with the fluctuation of lateral displacement of vehicles.

VI. CONCLUSION

In this paper, a traffic vehicle behavior prediction method based on game theory and Hidden Markov model is proposed, which studies the interaction between vehicle behaviors in traffic environment as a non-cooperative game. This paper first introduces some basic concepts of game theory, then designs the method framework of behavior prediction of traffic vehicles around the main vehicle based on expected utility theory, and gives the method of behavior prediction based on intention probability and behavior recognition results. In order to express the intention of the driver, the revenue function including the forward drivable space, the collision risk index and the riding comfort index is designed, In addition, GMM-HMM model parameters and revenue function parameters are trained by NGSIM traffic data set. Finally, in order to verify the advantages of the proposed behavior prediction method, two experiments are designed to compare the advantages of the proposed method with the traditional method under the scenario of road convergence. From the experimental results, it can be found that the method described in this paper can predict the future behavior of traffic vehicles earlier, at the same time, it can well reflect the interaction process of behavior between vehicles, and has better robustness.

REFERENCES

[1] H. Liu, T. Taniguchi, K. Takenaka, and T. Bando, "Defect-repairable latent feature extraction of driving behavior via a deep sparse autoencoder," *Sensors*, vol. 18, no. 2, p. 608, Feb. 2018.

[2] S. Atev, G. Miller, and N. P. Papanikolopoulos, "Clustering of vehicle trajectories," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 647–657, Sep. 2010.

[3] D. Vasquez and T. Fraichard, "Motion prediction for moving objects: A statistical approach," in *Proc. IEEE Int. Conf. Robot. Automat.*, New Orleans, America, Apr./May 2004, pp. 3931–3936.

[4] C. Tay, "Analysis of dynamic scenes: Application to driving assistance," *Chem. Pharmaceutical Bull.*, vol. 35, no. 35, pp. 5004–5009, 2009.

[5] G. S. Aoude, B. D. Luders, J. M. Joseph, N. Roy, and J. P. How, "Probabilistically safe motion planning to avoid dynamic obstacles with uncertain motion patterns," *Auton. Robots*, vol. 35, no. 1, pp. 51–76, Jul. 2013.

[6] W. Hu, X. Xiao, Z. Fu, D. Xie, T. Tan, and S. Maybank, "A system for learning statistical motion patterns," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 9, pp. 1450–1464, Sep. 2006.

[7] L. Huang, H. Guo, R. Zhang, H. Wang, and J. Wu, "Capturing drivers' lane changing behaviors on operational level by data driven methods," *IEEE Access*, vol. 6, pp. 57497–57506, 2018.

[8] A. Lawitzky, D. Althoff, and C. F. Passenberg, "Interactive scene prediction for automotive applications," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Gold Coast, QLD, Australia, Jun. 2013, pp. 1028–1033.

[9] G. Agamennoni, J. I. Nieto, and E. M. Nebot, "Estimation of multivehicle dynamics by considering contextual information," *IEEE Trans. Robot.*, vol. 28, no. 4, pp. 855–870, Aug. 2012.

[10] G. Agamennoni, J. I. Nieto, and E. M. Nebot, "A Bayesian approach for driving behavior inference," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2011, pp. 595–600.

[11] A. Martin, "Interactive motion prediction using game theory," M.S. thesis, Dept. Automat. Eng., Univ. Degli Studi di Padova, Padova, Italy, 2013.

[12] D. W. Oyler, Y. Yildiz, and A. R. Girard, "A game theoretical model of traffic with multiple interacting drivers for use in autonomous vehicle development," in *Proc. Amer. Control Conf. (ACC)*, Boston, MA, USA, Jul. 2016, pp. 1705–1710.

[13] R. B. Myerson, *Game Theory*. Cambridge, MA, USA: Harvard Univ. Press, 2013.

[14] N. J. Von and O. Morgenstern, *Theory of Games and Economic Behavior*. Princeton, NJ, USA: Princeton Univ. Press, 2007.

[15] C. Lin, G. Wu, and P. Pirozmand, "GTRF: A game theory approach for regulating node behavior in real-time wireless sensor networks," *Sensors*, vol. 15, no. 6, pp. 12932–12958, Jun. 2015.

[16] M. Land and O. Gefeller, "A game-theoretic approach to partitioning attributable risks in epidemiology," *Biometrical J.*, vol. 39, no. 7, pp. 777–792, 1997.

[17] M. J. Osborne and A. Rubinstein, *A Course in Game Theory*. Cambridge, MA, USA: MIT Press, 1994.

[18] M. A. Costa-Gomes, V. P. Crawford, and N. Iriberri, "Comparing models of strategic thinking in Van Huyck, Battalio, and Beil's coordination games," *J. Eur. Econ. Assoc.*, vol. 7, nos. 2–3, pp. 365–376, Apr. 2009.

[19] M. Althoff, O. Stursberg, and M. Buss, "Model-based probabilistic collision detection in autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 2, pp. 299–310, Jun. 2009.

[20] (2005). *U.S. Federal Highway Administration. U.S. I-80 Dataset*. Accessed: Jun. 6, 2017. [Online]. Available: https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm

[21] C. Thiemann, M. Treiber, and A. Kesting, "Estimating acceleration and lane-changing dynamics from next generation simulation trajectory data," *Transp. Res. Rec.*, vol. 2088, no. 1, pp. 90–101, Jan. 2008.

[22] X. Wang, J. Zhang, Y. Liu, W. Yunyun, F. Wang, and J. Wang, "The drivers' lane selection model based on mixed fuzzy many-person multi-objective non-cooperative game," *J. Intell. Fuzzy Syst.*, vol. 32, no. 6, pp. 4235–4246, May 2017.

[23] J. H. Yoo and R. Langari, "Stackelberg game based model of highway driving," in *Proc. ASME Dyn. Syst. Control Conf. (DSCC)*, Fort Lauderdale, FL, USA, Oct. 2012, pp. 499–508.
[24] A. Talebpour, H. S. Mahmassani, and S. H. Hamdar, "Modeling lane-changing behavior in a connected environment: A game theory approach," *Transp. Res. C, Emerg. Technol.*, vol. 59, pp. 216–232, Oct. 2015.
[25] J. H. Yoo, "A game theory based model of human driving with application to autonomous and mixed driving," Ph.D. dissertation, Dept. Mech. Eng., Texas A & M Univ., College Station, TX, USA, 2014.
[26] N. Li, D. W. Oyler, M. Zhang, Y. Yildiz, I. Kolmanovsky, and A. R. Girard, "Game theoretic modeling of driver and vehicle interactions for verification and validation of autonomous vehicle control systems," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 5, pp. 1782–1797, Sep. 2018.
[27] K. Jones, B. E. Bentley, J. M. Wood, and M. I. Woolf, "Application of parallax for the measurement of visibility distances in the open-road environment," in *Proc. Int. Arch. Photogram. Remote Sens.*, 1998, pp. 1–6.
[28] A. Campagne, T. Pebayle, and A. Muzet, "Correlation between driving errors and vigilance level: Influence of the driver's age," *Physiol. Behav.*, vol. 80, no. 4, pp. 515–524, Jan. 2004.
[29] Q. Jiang, "Threat assessment and trajectory planning for intelligent vehicle obstacle avoidance system," M.S. thesis, Dept. Vehi. Eng. Jilin Univ., Changchun, China, 2016.
[30] J. Wiest, M. Höffken, U. Kreßel, and K. Dietmayer, "Probabilistic trajectory prediction with Gaussian mixture models," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Alcala de Henares, Spain, Jun. 2012, pp. 141–146.
[31] C. Katrakazas, M. Quddus, W.-H. Chen, and L. Deka, "Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions," *Transp. Res. C, Emerg. Technol.*, vol. 60, pp. 416–442, Nov. 2015.
[32] W. Yao, H. Zhao, and F. Davoine, "Learning lane change trajectories from on-road driving data," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Alcala de Henares, Spain, Jun. 2012, pp. 885–890.
[33] P. Bajari, H. Hong, and S. P. Ryan, "Identification and estimation of a discrete game of complete information," *Econometrica*, vol. 78, no. 5, pp. 1529–1568, 2010.

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