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Modeling Driver's Car-Following Behavior Based on Hidden Markov Model and Model Predictive Control: A Cyber-Physical System Approach

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***Abstract*— The goal of this paper is to develop a novel moving horizon optimization modeling method of driver's car-following behavior based on hidden Markov model, which could effectively mimic driver's car-following process and driving characteristic. First, the analysis of relation between the driver's driving behavior and Markov random process is proposed, and the result of driver's desired driving behavior has the Markov property is proven. Then, a modeling framework with moving horizon optimization characteristic is presented, including the preview and perception module, prediction module, optimization module. In this framework, the hidden Markov model of driver's car-following behavior is given by taking the longitudinal acceleration as the hidden state and time headway as the output state. To obtain the longitudinal acceleration command, the optimization algorithm is used by maximizing the posterior probability. Finally, based on the NGSIM data set, the parameters of hidden Markov model are identified by the Baum-Welch algorithm, and the effectiveness and accuracy of proposed HMM-based modeling method are also discussed from the closed-loop responses of certain typical drivers.**

I. Introduction

Cyber-Physical Systems are multi-dimensional complex feedback systems, which expand the interaction between the cyber and physical worlds through the communication, computing and control technologies, and possibly with humans in the loop[1]. Intelligent transportation systems (ITS) as the special Cyber-Physical Systems have earned the sustained attention and interests in driver-oriented intelligent vehicles[2], which are motivated by their potentials for enhancements of driving safety, comfortable and efficiency. Understanding and modeling of human driving behavior under the complex driving scenarios became important issues to be studied, and received continuous interest in recent years[3,4].

The car-following characteristic is one of the main behaviors of human drivers in vehicle manipulation. The development of accurate driver's car-following behavior model could effectively understand the driver's driving process and mimic the driver's control action. Many longitudinal driver models have been presented in the previous researches. In [5], a "follow the leader model" was addressed, and the aim of the driver was to maintain a following distance from the leading vehicle. Based on the assumption that the driver's desired braking and acceleration rates were constrained, in [6], a new switching vehicle speed model was constructed for the following vehicle, and the driver's characteristics were represented by the parameters of model. In [7], to evaluate the performance of adaptive cruise control systems, an accurate longitudinal human driving model was developed, and six driver models were evaluated based on two selected databases. The research results illustrate that the Gipps model[6] was the most promising one, and a modified version of the model was also suggested and implemented in a microscopic traffic simulator, whose behavior was consistent with the macroscopic traffic one very well.

In the actual driving process, human drivers do not behave deterministically, some stochastic uncertainties were also exhibited[8]. This property attracts many researchers' attentions. In [9], An errorable car-following driver model was presented and modeled as a random process. To analyze and mimic the driver's driving behavior, the stochastic process method was applied, and the Road-Departure Crash-Warning System Field Operational Test data has been used to identify the model parameters and validate its effectiveness. From the results of a car-following experiment, it is shown that in [10], the driver's driving behavior can be represented by a simple scheme: the acceleration $a(t)$ is held approximately constant for a certain time interval, followed by a jump to a new acceleration. It also illustrates that the driver's behavior has deterministic and stochastic components[11].

In the process of driver's car-following, usually the vehicle movements can be observed and recorded, while the driver's behavior within vehicles can not be obtained directly. To derive unobservable driver behaviors, many modeling methods based on hidden Markov model (HMM) were developed. In [12], a HMM-based driver behavior model with layered structure was proposed. Meanwhile, the identification and evaluation algorithms of bad driving behavior were presented. In [13], HMM was also used to mimic the driver's various behaviors when driving at the crossing. To predict and simulate the driver's driving characteristics, the Intersection

Driver Support Project data was applied to evaluate the parameters of HMM. In [14], a HMM with two layers has been given to identify the driver's intention and predict the driving behavior. The effectiveness and accuracy of proposed HMM were proved by the test method of real time driving simulation.

Model predictive control (MPC)[15,16] and stochastic model predictive control (SMPC) have been increasingly implemented for vehicle control systems. In [17], mainly from Ford's perspectives, a concise review of the applications of MPC to vehicle control systems was provided, in which MPC-based driver prediction control was regarded as one of the major challenging topics. Many MPC-based or SMPC-based methods have been used to model the driver steering control[18,19] or driver predictive vehicle control. These research results illustrated that the moving horizon characteristic of MPC was consistent with the driver's driving process, and it could be used to mimic the driver's driving behavior effectively. In our previous researches [20, 21], several SMPC-based driver steering behavior models were presented, mainly from the assumption that the driver has the abilities of extracting the desired path, perception of the road friction, cognition of vehicle dynamics. In these studies, the longitudinal velocity of vehicle was assumed as a constant one. In fact, the driver need accelerate or decelerate the vehicle to adjust a suitable velocity, and there may have many uncertainties in this process, for example, the state information of leading car.

In this paper, a novel HMM-based modeling method of driver's car-following behavior with moving horizon optimization idea is presented, which can effectively capture and integrate the stochastic properties of driver's driving process. Our goal is to present a probabilistic receding horizon framework to understand the driver's driving process, and then to mimic the driver's behavior accurately.

The remainder of this paper is organized as follows. Section II presents the relation between the driver's driving process and HMM. Section III formulates the modeling method of driver's car-following behavior in detail. Section IV presents the simulations using NGSIM data. Section V concludes the study.

II. Analysis of Driver's Driving Intention and HMM

In this section, we first describe the definitions of stochastic process and Markov stochastic process, and then analyze the relation between the driver's driving intention and HMM.

Definition 1: For any parameter $t \in T$, $S(t, \omega)$ denotes as a random variable, and the family of random variables $S_T = \{S(t, \omega)\}$ is a stochastic process.

Definition 2: If for any $t_1 < t_2 \cdots < t_{N_S} < t$; s_i, $i = 1, 2, \cdots, N_S$, the stochastic process $\{S_t, t \in T\}$ satisfies the following condition:

$$\begin{aligned} &P(S_t = s_i | S_{t_1} = s_1, S_{t_2} = s_2, \cdots, S_{t_{N_S}} = s_{N_S}) \\ &= P(S_t = s_i | S_{t_{N_S}} = s_{N_S}) \end{aligned} \tag{1}$$

then the stochastic process $\{S_t, t \in T\}$ is called a Markov stochastic process.

The HMM $\lambda = (\mathcal{A}, \mathcal{B}, \Pi)$ is one kind of Markov model, its schematic diagram is shown in Fig.1. Normally, the state variables $\{S_i, i = 1, 2, \cdots, N_S\}$ can not be observed directly, which are the hidden ones in the Markov model. These state variables have the Markov property and can be reflected by the observable outputs $\{O_j, j = 1, 2, \cdots, N_O\}$. The probability transition matrix $\mathcal{A} = \{a_{ij}\}$ describes the transition probability of hidden states in HMM. The term $a_{ij} = P(S_{t+1} = j | S_t = i)$, $i, j = 1, 2, \cdots, N_S$ represents the probability of state $S_t = i$ at the time t transferred to state $S_{t+1} = j$ at the time $t+1$, N_S is the number of hidden states. The output probability transition matrix $\mathcal{B} = \{b_{ij}\}$ describes the relation between the observable outputs and the hidden states. The term $b_{ij} = P(O_t = i | S_t = j)$, $i = 1, 2, \cdots, N_S, j = 1, 2, \cdots, N_O$ represents the probability of observable output $O_t = i$ when the hidden state is $S_t = j$ at the time t, N_O is the number of observable outputs. $\Pi = (P(S_0 = 1), P(S_0 = 2), \cdots, P(S_0 = N_S))$ is the probability distribution of hidden states at the initial time.

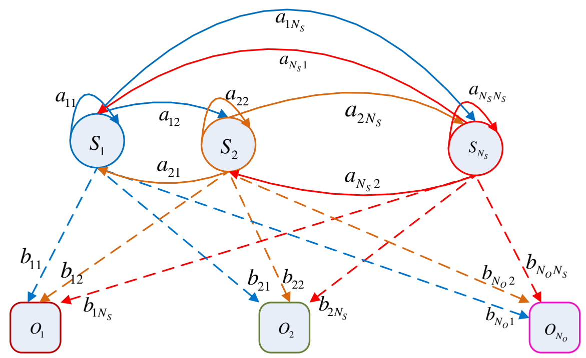

Fig. 1. Schematic of hidden Markov model.

Due to the impact of road condition, traffic information, weather and other factors, the driver's driving behavior is usually uncertain and time-varying. According to definition 1, the stochastic sequence of driver's driving behavior is a stochastic process. Further on the basis of theorem 1 and the results of Yang and Jost in [8, 9], the driver's driving behavior is described as a stochastic process with the Markov property.

Theorem 1: Suppose the stochastic process of driver's driving behavior $\{S_t, t \geq 0\}$ satisfies:

(i) $S_t = f(S_{t-1}, \xi_t)$, $(t \geq 1)$, with $f : \Im_1 \times \Im_2 \to \Im_1$, $\Im_1 = \{i_0, i_1, \cdots, i_t, \cdots\}$, the value of ξ_t is in the set $\Im_2$;

(ii) Stochastic process $\{\xi_t, t \geq 1\}$ is used to model the traffic uncertain information which would affect the driver's intention;

(iii) Suppose $\{\xi_t, t \geq 1\}$ are independent and identically distributed random variables, and S_0 is independent with $\{\xi_t, t \geq 1\}$.

Then $\{S_t, t \geq 1\}$ has the Markov property, and its one-step transition probability is

$$a_{ij} = P(f(i, \xi_1) = j). \tag{2}$$

Proof: Due to random variable ξ_{t+1} is independent with $S_0, S_1, \cdots, S_t$, then

$$\begin{aligned} & P(S_{t+1} = i_{t+1} | S_0 = i_0, \cdots, S_t = i_t) \\ = & P(f(S_t, \xi_{t+1}) = i_{t+1} | S_0 = i_0, \cdots, S_t = i_t) \\ = & P(f(i_t, \xi_{t+1}) = i_{t+1} | S_0 = i_0, \cdots, S_t = i_t) \\ = & P(f(i_t, \xi_{t+1}) = i_{t+1}). \end{aligned} \tag{3}$$

Similarly, it has

$$P(S_{t+1} = i_{t+1} | S_t = i_t) = P(f(i_t, \xi_{t+1}) = i_{t+1}). \tag{4}$$

Therefore, it can deduce that

$$\begin{aligned} & P(S_{t+1} = i_{t+1} | S_0 = i_0, \cdots, S_t = i_t) \\ = & P(S_{t+1} = i_{t+1} | S_t = i_t) \end{aligned} \tag{5}$$

which means $\{S_t, t \geq 0\}$ is a Markov stochastic process, and the one-step transition probability is (2). □

From theorem 1, it can be deduced that the driver's driving behavior has the Markov property, however, the driver's car-following behavior within vehicles can not be observed directly, they could be reflected by observable outputs, such as spacing or time headway. Here, spacing[11] is defined as "the distance, in feet, between two successive vehicles in a traffic lane, measured from the same common feature of the vehicles", it is shown in Fig. 2. Time headway[11] is defined as "the time, in seconds, between two successive vehicles as they pass a point on the roadway, measured from the same common feature of both vehicles". Time headway is represented by the mathematical symbol

$$T_h = \frac{x_l - x_f}{v_f} \tag{6}$$

where T_h is the time headway, x_l is the displacement of leading car, x_f is the displacement of following car, and v_f is the velocity of the following car.

Through the above analysis, the relation between the driver's car-following behavior and spacing/time headway, is consistent with the theory of HMM. In the following, we will discuss the modeling method to mimic the driver's car-following behavior based on HMM.

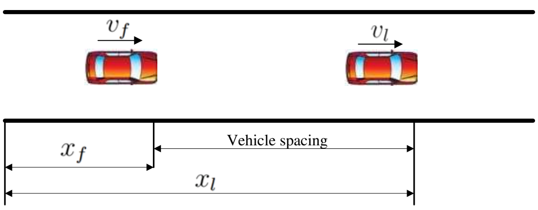

Fig. 2. Schematic of spacing and time headway between two consecutive vehicles.

III. Design of Driver's Car-Following Behavior Model

By observing front vehicle's states, host vehicle driver could obtain the information of spacing and time headway. Meanwhile, according to the current states of host vehicle and driving experiences, the driver has the ability of predicting the future states of host vehicle. To track the expected spacing and time headway, the driver will decide how to operate the vehicle in a sense of optimization. When the states of the front vehicle and host vehicle are updated, the driver will repeat the above process. Therefore, driver's car-following behavior has the moving horizon optimization characteristic, and the structure of based on HMM and MPC modeling method is given in Fig. 3.

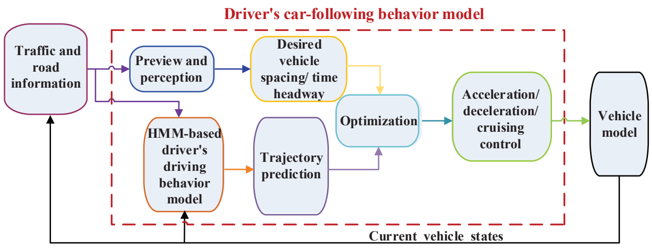

Fig. 3. HMM-based driver's car-following behavior modeling framework.

In the proposed modeling framework, preview and perception module is used to mimic the driver's behavior to perceive and estimate the desired spacing or time headway. Trajectory prediction module is mainly used to simulate the driver's ability of predicting the future trajectories of the vehicle, based on their own driving experiences and the current state of the vehicle. Optimization module is used to mimic the driver's control action which is generated by tracking the expected spacing or time headway. When the states of two vehicles reach the new ones, by moving horizon process of above modules, the objective of simulating the driver's car-following behavior is achieved.

A. HMM-based driver's driving behavior model

In this research, it is assumed that the driver does not steer the vehicle, but manipulate the accelerator pedal or brake pedal to change the vehicle's states. The continuous variable of longitudinal acceleration a_x can be selected to depict the driver's car-following behavior. However, from the discussion of Section II, the driver's car-following behavior can be simulated by HMM, which is the discrete random variable. To solve this problem, a method of discretization the interval of longitudinal acceleration is proposed. Specifically, assuming that the expected longitudinal acceleration of vehicle is in the interval $[a_{x_{\min}}, a_{x_{\max}}]$. By selecting the number of partition N_S, the interval $[a_{x_{\min}}, a_{x_{\max}}]$ can be divided into N_S subintervals. Here, N_S is corresponding to the number of hidden states in HMM. When the desired longitudinal acceleration is optimized and located in the i-th subinterval $[a_{x_{i-1}}, a_{x_i})$, then the driver's driving behavior is related to the index $S = i$. Obviously, the larger the number of selected partition N_S, the more denser the partition $[a_{x_{\min}}, a_{x_{\max}}]$. Thus, the description of driver's driving behavior will become more accurate.

Based on the above discretization method, assume that the probability distribution $\Pi = (p_i)$ is

$$P(S_t = i) = p_i, \quad i = 1, 2, \cdots, N_S, \tag{7}$$

where $p_1 + p_2 + \cdots + p_{N_S} = 1$.

The probability of a driver's driving behavior is transferred from one state to another could be depicted by the probability transition matrix $\mathcal{A}_{N_S \times N_S}$

$$\mathcal{A} = \begin{pmatrix} a_{11} & a_{12} & \cdots & \cdots & a_{1N_S} \\ a_{21} & a_{22} & \cdots & \cdots & a_{2N_S} \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ a_{N_S 1} & a_{N_S 2} & \cdots & \cdots & a_{N_S N_S} \end{pmatrix} \tag{8}$$

where $a_{ij} = P(S_{t+1} = j | S_t = i)$ represents the probability that the longitudinal acceleration of vehicle is transferred from the i-th interval $[a_{x_{i-1}}, a_{x_i})$ at the time t, to the j-th interval $[a_{x_{j-1}}, a_{x_j})$ at the time $t+1$.

Though the driver's driving behavior within the car can not be observed, it could be represented by spacing or time headway. In this paper, the time headway is chosen as the observable output state. This is because, from eq. (6), the information of time headway contains not only the spacing of two vehicles, but also the longitudinal velocity of vehicle. Similarly, the above discretization method is applied to divide the interval $[T_{h_{\min}}, T_{h_{\max}}]$ into N_O subintervals. Here, N_O is the same as the number of observable output states in HMM. That the expected time headway T_h is in the i-th interval $[T_{h_{i-1}}, T_{h_i})$ implies the current output state is $O = i$.

In our research, the conditional probability $b_{ij} = P(O_t = i | S_t = j)$ is adopted to describe the relation between driver's behavior and time headway. The conditional probability b_{ij} represents the probability that the driver's driving behavior at the time t is in the j-th interval $[a_{x_{j-1}}, a_{x_j})$, and the output state of time headway is in the i-th interval $[T_{h_{i-1}}, T_{h_i})$. Moreover, the probability transition matrix $\mathcal{B}_{N_O \times N_S}$ of output states is defined by

$$\mathcal{B} = \begin{pmatrix} b_{11} & b_{12} & \cdots & \cdots & b_{1N_S} \\ b_{21} & b_{22} & \cdots & \cdots & b_{2N_S} \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ b_{N_O 1} & b_{N_O 2} & \cdots & \cdots & b_{N_O N_S} \end{pmatrix} \tag{9}$$

Above all, the process of applying HMM $\lambda = (\mathcal{A}, \mathcal{B}, \Pi)$ to mimic the driver's driving intention could be depicted as

$$\mathbb{S}_{k+1} = \mathcal{A}\mathbb{S}_k \tag{10a}$$

$$\mathbb{O}_k = \mathcal{B}\mathbb{S}_k \tag{10b}$$

where

$$\mathbb{S}_k = (S_{k1}, S_{k2}, \cdots, S_{kN_S})^T, \tag{11}$$

$$\mathbb{O}_k = (O_{k1}, O_{k2}, \cdots, O_{kN_O})^T. \tag{12}$$

B. Modeling the driver's preview, prediction and optimization behavior

Preview: In the process of car-following, the driver has the ability to observe and perceive the traffic information. To prevent collision with the leading car, driver usually maintains a safe distance from the leading one. From the driver's abilities of preview and perception, the expected sequence of time headway $(T_{h_d}(k+1), T_{h_d}(k+2), \cdots, T_{h_d}(k+N_p))$ can be obtained, where N_p represents the number of preview points.

Prediction: Meanwhile, based on their own driving experiences and the current states of vehicle, the driver has the ability to predict the future states of the vehicle within a period of time. From (10) and the current states of vehicle, the predicted output sequence is

$$\mathcal{O}_p(k) = (\mathbb{O}_{p_{k+1}}, \mathbb{O}_{p_{k+2}}, \cdots, \mathbb{O}_{p_{k+N_p}}) \tag{13}$$

where $\mathbb{O}_{p_{k+i}} = \mathcal{B}\mathbb{S}_{k+i} = \mathcal{B}\mathcal{A}^i\mathbb{S}_k, i = 1, 2, \cdots, N_p$.

Optimization: In order to track the expected time headway between two vehicles, the driver needs to find the most probable sequence of desired events, which is the sequence of hidden states (equivalent to longitudinal acceleration). In this research, when the HMM $\lambda = (\mathcal{A}, \mathcal{B}, \Pi)$ has been established, the Viterbi algorithm is utilized to generate the sequence of driver's driving behavior, and then to track the expected time headway. The formed optimization problem is as follows:

Problem 1:

$$\max_{\mathcal{S}(k) \in \mathbf{S}} P(\mathcal{S}(k) \mid \mathcal{O}_p(k) = \mathcal{O}_d(k)) \tag{14a}$$

$$\text{Subject to:} \quad \begin{cases} \mathbb{S}_{k+1} = \mathcal{A}\mathbb{S}_k \\ \mathbb{O}_k = \mathcal{B}\mathbb{S}_k \end{cases} \tag{14b}$$

where, $\mathcal{S}(k) = (\mathbb{S}_{k+1}, \mathbb{S}_{k+2}, \cdots, \mathbb{S}_{k+N_p})$ is the sequence of driver's driving behavior which is to be optimized (equivalent to the control input sequence of vehicle), $\mathcal{O}_d(k) = (\mathbb{O}_{d_{k+1}}, \mathbb{O}_{d_{k+2}}, \cdots, \mathbb{O}_{d_{k+N_p}})$ represents the expected output sequence, which is also the sequence of the expected time headway.

According to Bayes formula

$$P(\mathcal{S}(k) \mid \mathcal{O}_d(k)) = \frac{P(\mathcal{S}(k))P(\mathcal{O}_d(k)|\mathcal{S}(k))}{P(\mathcal{O}_d(k))} \tag{15}$$

actually, there is no relation between the value of the conditional probability $P(\mathcal{S}(k) \mid \mathcal{O}_d(k))$ and the value of $P(\mathcal{O}_d(k))$, when the expected output sequence $\mathcal{O}_d(k)$ is known. Therefore, the maximum value of the conditional probability $P(\mathcal{S}(k) \mid \mathcal{O}_d(k))$ could be equivalent to the maximum value of the following function

$$V(\mathcal{S}(k)) = P(\mathcal{S}(k))P(\mathcal{O}_d(k)|\mathcal{S}(k)). \tag{16}$$

Next, we will describe the process of solving Problem 1.

(a) When $N_p = 1$, define

$$V_{k+1} = P(\mathbb{S}_{k+1})P(\mathbb{O}_{d_{k+1}}|\mathbb{S}_{k+1}), \tag{17}$$

then

$$\mathbb{S}^*_{k+1} = \arg\max_{\mathbb{S}_{k+1} \in \mathcal{S}} V_{k+1}. \tag{18}$$

(b) When $N_p = 2$, define

$$\begin{aligned} V_{k+2} &= P(\mathbb{S}_{k+1}, \mathbb{S}_{k+2}) P(\mathbb{O}_{d_{k+1}}, \mathbb{O}_{d_{k+2}} | \mathbb{S}_{k+1}, \mathbb{S}_{k+2}) \\ &= P(\mathbb{O}_{d_{k+2}} \mid \mathbb{S}_{k+2}) P(\mathbb{S}_{k+2} \mid \mathbb{S}_{k+1}) \times \\ &\qquad\qquad P(\mathbb{S}_{k+1}) P(\mathbb{O}_{d_{k+1}} \mid \mathbb{S}_{k+1}) \\ &= P(\mathbb{O}_{d_{k+2}} \mid \mathbb{S}_{k+2}) P(\mathbb{S}_{k+2} \mid \mathbb{S}_{k+1}) V_{k+1}, \end{aligned} \tag{19}$$

then

$$(\mathbb{S}^*_{k+1}, \mathbb{S}^*_{k+2}) = \underset{(\mathbb{S}_{k+1}, \mathbb{S}_{k+2}) \in \mathcal{S}}{\arg\max} \; V_{k+2} \tag{20}$$

$$\vdots$$

(c) When $N_p = N_p$, define

$$\begin{aligned} V_{k+N_p} &= P(\mathcal{S}(k)) P(\mathcal{O}_d(k) \mid \mathcal{S}(k)) \qquad (21) \\ &= P(\mathbb{O}_{d_{k+N_p}} \mid \mathbb{S}_{k+N_p}) P(\mathbb{S}_{k+N_p} \mid \mathbb{S}_{k+N_p-1}) V_{k+N_p-1} \end{aligned}$$

then

$$(\mathbb{S}^*_{k+1}, \cdots, \mathbb{S}^*_{k+N_p}) = \underset{(\mathbb{S}_{k+1}, \cdots, \mathbb{S}_{k+N_p}) \in \mathcal{S}}{\arg\max} \; V_{k+N_p} \tag{22}$$

IV. Simulation of Driver's Car-Following Behavior

In this part, the closed-loop responses of certain typical drivers are analyzed and studied by applying the HMM-based moving horizon optimization method. Here, the vehicles with ID numbers 94, 680, 1084, 2019 from the Next Generation Simulation (NGSIM) trajectory data are chosen as the cases to study.

Note that HMM is a discrete process, the optimized sequence of driver's driving behavior would be a series of discrete values. Though the range of driver's driving behavior is known from this interval, the accurate value of longitudinal acceleration which is acted directly on vehicle can not be obtained. Here, a stochastic approximation method is adopted. Specifically, if the first element of optimized driving intention sequence at the time k is i, which means the value of longitudinal acceleration is in the i-th interval $[a_{x_{i-1}}, a_{x_i})$, then the random value which is used to taken as the current longitudinal acceleration, is given below:

$$a_x(k) = (a_{x_i} - a_{x_{i-1}}) \times rand(1) + a_{x_i} \tag{23}$$

where $rand(1)$ represents the uniform random number in the interval $[0, 1]$.

Remark 4.1: It seems that the value of vehicle longitudinal acceleration obtained from (23) may be any one in the interval $[a_{x_{i-1}}, a_{x_i})$. So it will lead to certain deviation from the real value. As the number of partition increases, the range of each interval will be smaller, to a certain extent, the deviation may be reduced. However, when the selected number of partition is too much, the dimensions of state probability distribution, state probability transition matrix and output probability transition matrix will be also larger. This may affect not only the speed of calculation, but also the regularity of data distribution. At present, the proposed modeling method of driver's car-following behavior can not completely eliminate this deviation.

A detailed division of vehicle longitudinal acceleration and time headway for the four typical vehicles is made. The results are shown in Table I. After this division, according to Baum-Welch algorithm, the probability distribution Π, probability transition matrix $\mathcal{A}$ and output probability transition matrix $\mathcal{B}$ of vehicle longitudinal acceleration can be calculated.

TABLE I

DIVISION OF VEHICLE LONGITUDINAL ACCELERATION AND TIME HEADWAY

ID	a_x (m/s^2)	N_S	T_h (s)	N_O	N
94	$[-0.32, 0.4]$	36	$[1, 12]$	22	791
1084	$[-0.32, 0.48]$	40	$[1, 12]$	22	658
2019	$[-0.32, 0.26]$	58	$[0.5, 3]$	25	1183
680	$[-0.37, 0.17]$	54	$[0.95, 2.45]$	30	754

For the proposed HMM-based driver's car-following behavior model, the closed-loop response curves of four typical vehicles can be obtained. Comparison results of vehicle longitudinal velocity between the simulation one and the real one are shown in Figs.4-7. The blue solid line shows the real data, and the red dotted line represents the simulation one. It can be seen from the comparison results, no matter the vehicle is in the acceleration phase or deceleration phase, the red dotted lines are able to track the main tendency of the blue solid lines, and the consistency is relatively well. These indicate that the proposed HMM-based driver's car-following behavior model could mimic the driving process of real driver accurately.

There may be three main reasons for the deviation between the simulation and recorded data:

(1) In the recorded data, the sample points contained in the data set of individual trajectory are relatively small, the most one has only 1183 groups;

(2) In the process of interval division and the restoration of vehicle longitudinal acceleration, there exists certain deviations inevitably;

(3) The Viterbi optimization algorithm is an optimization process which is maximizing the posterior probability, this leads to the obtained results are only the optimal one in the probabilistic sense.

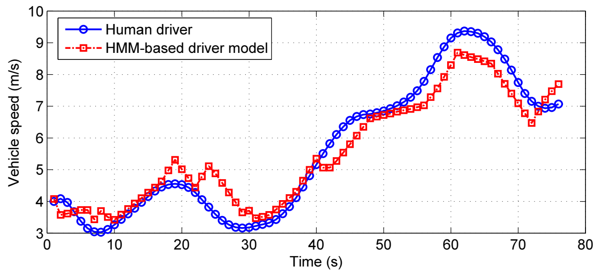

Fig. 4. Comparison results of simulation and actual longitudinal velocity for ID 94 vehicle.

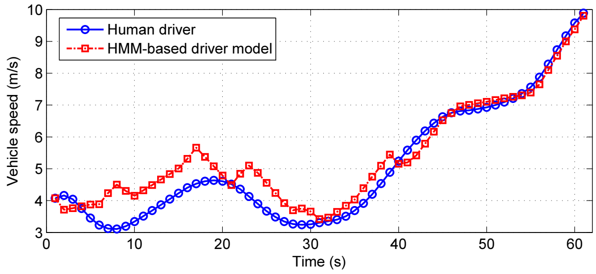

Fig. 5. Comparison results of simulation and actual longitudinal velocity for ID 1084 vehicle.

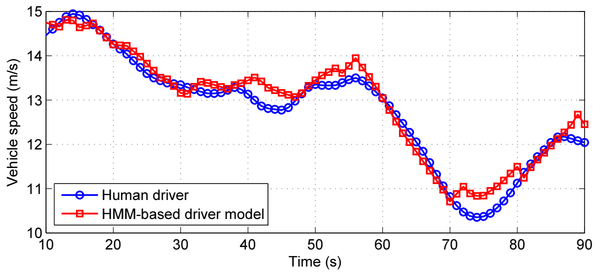

Fig. 6. Comparison results of simulation and actual longitudinal velocity for ID 2019 vehicle.

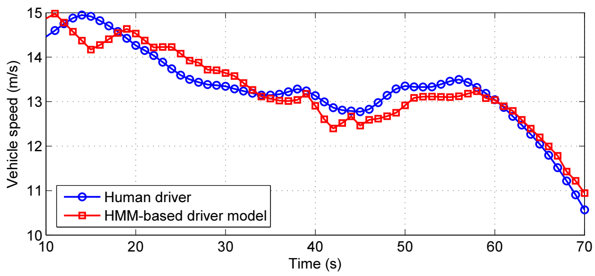

Fig. 7. Comparison results of simulation and actual longitudinal velocity for ID 680 vehicle.

V. Conclusions

In this research, we developed a modeling framework with moving horizon optimization characteristic to mimic driver's car-following behavior, and presented a novel HMM-based modeling method. The driver's driving process has the Markov property was proven. Analysis and simulation results of longitudinal velocity data for typical driver's car-following behavior were provided, and the performance of the proposed modeling method was illustrated by multiple groups of comparisons. From our research, it seems that the HMM-based moving horizon optimization modeling method is a feasible and effective one, which could effectively mimic driver's driving process, and it may also provide new insights into better understanding of the driver's car-following behavior.

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