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A driving intention prediction method based on hidden Markov model for autonomous driving

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ABSTRACT

In a mixed-traffic scenario where both autonomous vehicles and human-driving vehicles exist, a timely prediction of driving intentions of nearby human-driving vehicles is essential for the safe and efficient driving of an autonomous vehicle. In this paper, a driving intention prediction method based on hidden Markov model (HMM) is proposed for autonomous vehicles. HMMs representing different driving intentions are trained and tested with field collected data from a flyover. When training the models, either discrete or continuous characterization of the mobility features of vehicles is applied. Experimental results show that the proposed method performs better than the logistic regression (LR) method, and the HMMs trained with the continuous characterization of mobility features can give a higher prediction accuracy when they are used for predicting driving intentions. Moreover, when the surrounding traffic of the vehicle is taken into account, the performances of the proposed prediction method are further improved.

1. Introduction

Traffic safety has always been one of the important issues in human society. With the development of autonomous driving technology, a mixed-traffic urban environment is arising, in which autonomous vehicles have to interact with human-driven vehicles [1]. In the interaction between autonomous and human-driven vehicles, how to avoid traffic accidents caused by unmanned driving has become a research field of great concern [2]. Generally, autonomous vehicles have to make decisions in dynamic and uncertain environments. The uncertainty comes from the fact that the intention of human drivers cannot be directly measured [3]. Hence, for an unmanned vehicle, the accurate prediction of the expected behavior of other vehicles is essential to avoid the threat of traffic accidents. In the traditional traffic scenario where only human-driven vehicles exist, human drivers can judge the moving intentions of the surrounding vehicles according to the established traffic rules and their driving experience. Based on the judgment, each driver adjusts his/her driving in real time, in order to ensure the safety and efficiency of the traffic. However, in the mixed-traffic scenario, the unmanned vehicles have to estimate the driving intentions of the human-driven vehicles on the road based on pre-established prediction models. For an unmanned vehicle, it can obtain the driving status of another vehicle on the road based on communication techniques such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [4,5]. Research on the communication techniques in vehicular networks has been widely carried out, including the resource allocation in vehicular networks [6–10], which can guarantee reliable communications among unmanned vehicles and human-driven vehicles. With the driving status of nearby vehicles obtained via communications, an unmanned vehicle can apply the pre-established prediction model to predict the future driving intentions of the nearby vehicles [11].

In recent years, researchers have been working on the recognition and prediction of driving intentions of vehicles. For example, Bayesian decision, support vector machine (SVM), and hidden Markov model (HMM) etc., are widely used. In [12], the authors proposed an algorithm to predict driver's intention with fuzzy logic and edit distance. In [13] and [14], SVM is implemented for driving intention recognition. The model for detecting cognitive distraction is developed using drivers' eye movements and driving performance data. HMMs are applicable in characterizing the underlying relationship between observations and the hidden states that generate the observations. The authors in [15] proposed a method of modeling driving behavior concerned with a certain period of past movements by using AR-HMM, in order to predict the stop probability of a vehicle. The methods developed in [16] can be applied in ADAS to take appropriate measures in reducing accidents. The driver intention close to a road intersection is estimated, using discrete HMMs and the Hybrid State System (HSS) framework as basis. The driver decisions are depicted as a discrete state system at a higher level and the continuous vehicle dynamics are

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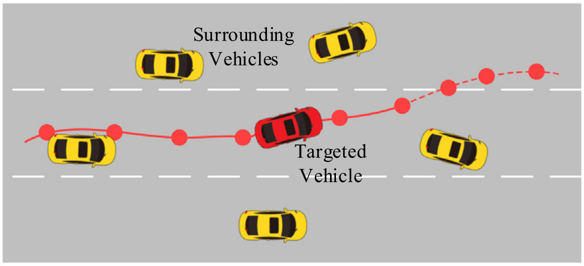

Fig. 1. The targeted vehicle and the surrounding vehicles.

depicted as a continuous state system at a lower level in the HSS framework. The study in [17] focuses on the scenario when vehicles merge because of reduction in the number of lanes on city roads, and considers the mutual interaction between drivers. However, the mobility data of vehicles used in most existing work is generated by driving simulators, which cannot accurately reflect the driving conditions of the vehicle in the real traffic environment.

In our work, the traffic data is collected from vehicles on a real road. When predicting the driving intention of a vehicle on this road, its historical movement trajectory is first considered, and then the surrounding traffic close to it is taken into account. Firstly, we use the collected data to train the prediction model based on HMM. Then, we use the trained model to predict the driving intention of a given vehicle. In this paper, the given vehicle is considered as the targeted vehicle, and the vehicles nearby are considered as the surrounding vehicles. When a trail of historical information of the targeted vehicle, or information of both the targeted vehicle and the surrounding vehicles is available, the most likely future driving intention of the targeted vehicle can be achieved through the proposed method. Moreover, either discrete or continuous characterization of this mobility information is applied to make the mobility features be used as observations in HMMs. In the discrete characterization, K-means clustering is used for discretizing the mobility data of vehicles. In the continuous characterization, the continuous mobility features are modeled as Gaussian mixture models (GMMs).

The main contributions of this paper are summarized as follows.

- A driving intention prediction method is proposed based on HMM, which can be used to predict the future moving intention of a given targeted vehicle, when a trail of mobility features is available.
- The HMMs are trained with data collected from the vehicles on a real road, and can be better adapted to the real traffic environment.
- The prediction is carried out in the case where only the targeted vehicle is involved in, and in the case where both the targeted vehicle and the surrounding vehicles are involved in. When the mobility features of the surrounding vehicles are introduced, the performances of the proposed prediction method are further improved.

The rest of this paper is organized as follows. In Section II, we propose a driving intention prediction method based on HMM. The experiment scenario and numerical results are given in Section III. Section IV concludes this paper.

2. Prediction of driving intentions based on HMM

In this section, we propose a driving intention prediction method based on HMM. The vehicle whose driving intention is required to be predicted is referred as the targeted vehicle, and the vehicles close to it are referred as surrounding vehicles, as shown in Fig. 1. The process of the proposed method is illustrated in Fig. 2. The trails of mobility features of vehicles are obtained, and the training of HMMs can be implemented in one of the two approaches. On one hand, in the HMM training with the discrete characterization of mobility features, all the trails of features are firstly turned into observation sequences. After that, they are divided into a training set and a test set. The vehicles in the training set are classified into three subsets, according to the driving intentions. Finally, HMMs representing different driving intentions are trained. On the other hand, in the HMM training with the continuous characterization of mobility features, the training set is firstly divided into subsets, and then the continuous characterization and the training of HMMs are processed at the same time. After the HMMs are well trained with one of the two approaches, vehicles in the test set can be used to test the models. In each experiment, the driving intention of one vehicle from the test set is predicted. The prediction accuracy is statistically measured among all experiments. The following subsections describe each step in detail.

2.1. Mobility features of vehicles

Information from the targeted vehicle and the surrounding vehicles can be used as features for HMM training and prediction. Firstly, the dataset provides dynamic locations of the vehicles on a selected road. For a particular vehicle, its location coordinates are recorded every certain seconds, and a successive trail of its locations is available. Moreover, in another dataset, the lanes of the roads are divided into segmented links, and the location coordinates of each link are provided. Then, by preprocessing the raw data, some types of mobility features such as velocity, acceleration of the vehicles, and the offsets between the vehicles and the lanes can be obtained. Finally, several types of mobility features are selected and used in HMM training and prediction.

In this paper, N types of mobility features are selected for each vehicle in the HMM training and prediction. The trail of the nth type of feature is denoted as a vector, i.e.,

$$\mathbf{x}_n = [x_{n,1}, \dots, x_{n,t}, \dots, x_{n,T}], \tag{1}$$

where $t = 1, 2, \dots, T$ is the index of the time step. It is assumed that the trails of all types of features are truncated to the same length of T time steps. Then, the set of all types of features of this vehicle can be written as a matrix, i.e.,

$$\mathbf{X} = [\mathbf{x}_1^{\mathsf{T}}, \dots, \mathbf{x}_n^{\mathsf{T}}, \dots, \mathbf{x}_N^{\mathsf{T}}], \tag{2}$$

where $n = 1, 2, \dots, N$.

Note that $\mathbf{X}$ defined above is a matrix representing a set of features for one vehicle. Generally, to make an HMM converged in the training, an adequate number of samples are required. Assume that L vehicles are used to train an HMM, and let $\mathbf{X}^l$ denote the set of features of the lth vehicle. Thus, a matrix $\mathbf{F} = [\mathbf{X}^1; \dots; \mathbf{X}^l; \dots; \mathbf{X}^L]$ has a dimension of $TL \times N$, and it is the matrix that includes the mobility features of all L vehicles, namely mobility feature matrix. Note that the mobility feature matrix can include the mobility features of both the targeted vehicle and the surrounding vehicles.

2.2. HMM training with discrete characterization of mobility features

The mobility features can be represented in a discrete form by the technique of clustering. One possible approach is to apply K-means clustering, which is an exclusive clustering method based on distance. It classifies the sets of mobility features into K clusters via unsupervised machine learning technique, and outputs the index of the cluster that each set belongs to [18,19].

Algorithm 1. Discrete characterization of mobility features by K-means clustering

Input: mobility feature matrix $\mathbf{F}$, number of clusters K.
Output: observation sequences of L vehicles $O = \{O^1, \dots, O^l, \dots, O^L\}$.
Initialization:

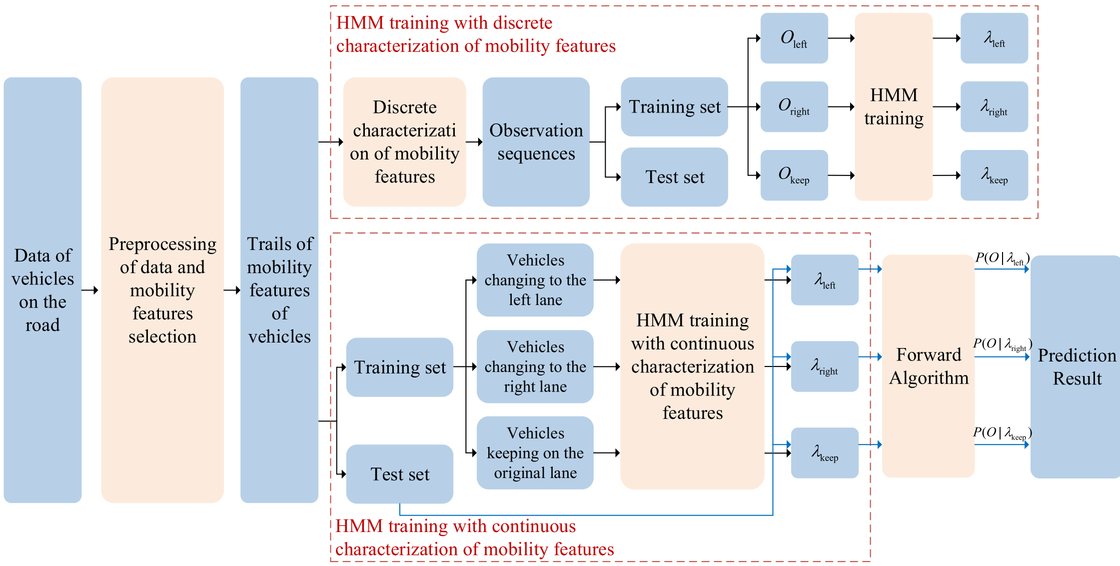

Fig. 2. The framework of the proposed driving intention prediction method.

Set initial values of the center points of the clusters: $\mu_1, \mu_2, \ldots, \mu_K$.

Step 1:

For any data point c_d, classify it into cluster k, if the center point of the cluster k is the nearest one of all K center points to it.

Step 2:

Update $r_{d,k}$ according to the classification result;

Update the values of center points μ_k by (4).

Step 3:

IF μ_k converges, denote the final classification result as $y(d) = k$ when $r_{d,k} = 1$; The observation of each vehicle O^l is obtained by $o_t^l = y[(l-1)T + t]$, where o_t^l is the element of O^l at time step t;

ELSE Return to **Step 1**.

As discussed above, the mobility features of L vehicles are involved, and each vehicle gives a set of features at each time step. Thus, there are TL sets of features, and each set c_d is the dth row of mobility feature matrix $\mathbf{F}$, where $d = 1, 2, \ldots, TL$. Each c_d is regarded as a data point in the N-dimensional space, and should be classified into one of the K clusters in the space. The main idea is to minimize the sum of distance from the center points to the data points in the clusters. Let μ_k represent for the center point of cluster k, the sum of distance is denoted as

$$J = \sum_{d=1}^{TL} \sum_{k=1}^{K} r_{d,k} \left\| c_d - \mu_k \right\|, \tag{3}$$

where $r_{d,k} = 1$ if c_d is classified into the kth cluster and $r_{d,k} = 0$ otherwise. To ensure that J is minimized, μ_k should meet

$$\mu_k = \frac{\sum_{d=1}^{TL} r_{d,k} c_d}{\sum_{d=1}^{TL} r_{d,k}}, \tag{4}$$

where $k = 1, 2, \ldots, K$. The detailed procedure of discrete characterization of mobility features by K-means clustering is described in Algorithm 1.

In this paper, one particular HMM λ_i is trained for each type of driving intention $i = 1, 2, \ldots, I$, where I is the number of types of driving intention. For an HMM λ (the index i is omitted for simplicity), it includes a set of hidden states H, a set of observations V, state transition probabilities $A = \{a_{q,p}\}$, state-observation probabilities $B = \{b_q(j)\}$, and initial state probabilities $\pi = \{\pi_q\}$ [20,21]. It can be represented as

$$\lambda = \{H, V, A, B, \pi\}. \tag{5}$$

It is assumed that there are Q possible hidden states in the set H. The hidden states might be the inside operations by the drivers that causes changes in the observations.

Given an HMM, the forward probability $\alpha_t(q)$ is defined as the probability of observing $o_1^l, o_2^l, \ldots, o_t^l$ and the state of the Markov chain at time t being the qth state in the H, i.e.,

$$\alpha_t(q) = P(o_1^l, o_2^l, \ldots, o_t^l, s_t = H(q)|\lambda). \tag{6}$$

Similarly, the backward probability $\beta_t(q)$ is defined as

$$\beta_t(q) = P(o_{t+1}^l, o_{t+2}^l, \ldots, o_T^l, s_t = H(q)|\lambda). \tag{7}$$

Then, the probability of the state at time t being $H(q)$ is

$$\eta_t(q) = \frac{\alpha_t(q)\beta_t(p)}{\sum_{p=1}^{Q} \alpha_t(p)\beta_t(p)}. \tag{8}$$

The probability of the state at time t being $H(q)$ and the state at time $t+1$ being $H(p)$ can be obtained, i.e.,

$$\xi_t(q,p) = \frac{\alpha_t(q) a_{q,p} b_q(o_{t+1}^l) \beta_{t+1}(p)}{\sum_{q=1}^{Q} \sum_{p=1}^{Q} \alpha_t(q) a_{q,p} b_q(o_{t+1}^l) \beta_{t+1}(p)}. \tag{9}$$

As discussed above, when applying K-means clustering, the trail of mobility features of vehicle l is turned into one an observation sequence of integers, i.e., O^l. After that, Baum-Welch algorithm is applied in this paper for the training of HMMs. To ensure the convergence in the training of an HMM λ_i, observations of L_i vehicles are used. For simplicity, the index i is omitted, and the input of the training algorithm is denoted as a set of observations $O = \{O^1, \ldots, O^l, \ldots, O^L\}$. The parameters of the HMM are estimated in the iteration of training process. Algorithm 2 gives the detailed procedure of HMM training in the case of discrete characterization of mobility features.

Algorithm 2. HMM training with discrete characterization of mobility features

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Input: observation sequences of L vehicles $O = \{O^1, \ldots, O^l, \ldots, O^L\}$.

Output: HMM parameters A, B, π.

Initialization:

Initial guess of A, B, π: $\tilde{a}_{q,p}^{(0)}, \tilde{b}_p(j)^{(0)}, \tilde{\pi}_q^{(0)}$;

$l = 1$.

Step 1:

Use O^l and the values of HMM parameters to obtain $\eta_t(q)^{(l)}$ and $\xi_t(q,p)^{(l)}$ by (13)–(14);

The state transition probability of sequence O^l: $a_{q,p}^{(l)} = \frac{\sum_{t=1}^{T} \xi_t(q,p)^{(l)}}{\sum_{t=1}^{T-1} \eta_t(q)^{(l)}}$;

5: The state-observation probability of sequence O^l:

$$b_p(j)^{(l)} = \frac{\sum_{t=1, o_t^l = V(j)}^{T} \eta_t(p)^{(l)}}{\sum_{t=1}^{T} \eta_t(p)^{(l)}};$$

6: The initial state probability of sequence O^l: $\pi_q^{(l)} = \eta_1(q)^{(l)}$.

Step 2:

7: Update A by $\tilde{a}_{q,p}^{(l)} = \frac{1}{l}\sum_{i=1}^{l} a_{q,p}^{(l)}$;

8: Update B by $\tilde{b}_p(j)^{(l)} = \frac{1}{l}\sum_{i=1}^{l} b_p(j)^{(l)}$;

9: Update π by $\tilde{\pi}_q^{(l)} = \frac{1}{l}\sum_{i=1}^{l} \pi_q^{(l)}$;

10: $l = l + 1$.

Step 3:

11: **IF** A, B and π converge, or $l = L$ is met, output $\lambda = \{A, B, \pi\}$;

12: **ELSE** Return to **Step 1**.

2.3. HMM training with continuous characterization of mobility features

The process of clustering in the discrete characterization turns the trails of mobility features into sequences of integers, and then the state-observation probabilities can be written in the form of a matrix, i.e., B. However, this may cause a loss of information in continuous data, especially when the number of clusters is relatively small. Gaussian mixture model can be used as an alternative approach to characterize the continuous mobility features in HMM training. The nth column of $\mathbf{F}$ is the vector that includes the trails of features of type n of all L vehicles, which can be denoted as $\mathbf{f}_n$, with the probability density function of $p(\mathbf{f}_n)$. Then, a superposition of M Gaussian distribution is used to fit $p(\mathbf{f}_n)$, i.e.,

$$p(\mathbf{f}_n) = \sum_{m=1}^{M}\sum_{p=1}^{Q} \omega_{n,p,m} p(\mathbf{f}_n | \mathcal{N}(\mu_{n,p,m}, \sigma_{n,p,m})), \tag{10}$$

where $\omega_{n,p,m}$ is the weight that the pth state is modeled by the mth Gaussian component for mobility feature of type n, $\mu_{n,p,m}$ and $\sigma_{n,p,m}$ are the corresponding mean value and standard deviation of the Gaussian distribution respectively. Use a set $\Theta_n = \{\Omega_n, \mathrm{M}_n, \Sigma_n\}$ to represent the GMM parameters for the nth type of feature, where $\Omega_n = \{\omega_{n,p,m}\}$, $\mathrm{M}_n = \{\mu_{n,p,m}\}$ and $\Sigma_n = \{\sigma_{n,p,m}\}$ are three 3-dimensional matrices. Then, we denote $\Theta = \{\Theta_1, \Theta_2, \ldots, \Theta_N\}$ as the set of GMM parameters for the completed N types of mobility features.

In the HMM training with continuous characterization of mobility features, maximum likelihood estimation is applied to compute the GMM parameters. The objective is to find the Gaussian distributions that are most likely to fit the probability density functions of the mobility features. For the nth type of feature, it is required to find the Θ_n which satisfies

$$\arg\max_{\Theta_n} p(\mathbf{f}_n) = \arg\max_{\Theta_n} \prod_{t}^{TL} p(\mathbf{f}_n(t)). \tag{11}$$

To obtain the required GMM parameters [22], an initial guess of Θ is set, and then the probability of the value $\mathbf{f}_n(t)$ produced by the mth Gaussian component is

$$\gamma_{n,p,m,t} = \frac{\sum_{p=1}^{Q} \omega_{n,p,m}\mathcal{N}(\mathbf{f}_n(\mathrm{t})|\mu_{n,p,m}, \sigma_{n,p,m})}{\sum_{p=1}^{Q}\sum_{j=1}^{M} \omega_{n,p,j}\mathcal{N}(\mathbf{f}_n(\mathrm{t})|\mu_{n,p,j}, \sigma_{n,p,j})}. \tag{12}$$

The corresponding mean value and standard deviation can be achieved, i.e.,

$$\mu_{n,p,m} = \frac{\sum_{t=1}^{TL} \mathbf{f}_n(t)\gamma_{n,p,m,t}}{\sum_{t=1}^{TL} \gamma_{n,p,m,t}}, \tag{13}$$

$$\sigma_{n,p,m}^2 = \frac{\sum_{t=1}^{TL} (\mathbf{f}_n(t) - \mu_{n,p,m})^2 \gamma_{n,p,m,t}}{\sum_{t=1}^{TL} \gamma_{n,p,m,t}}. \tag{14}$$

In this case, the state-observation probabilities are represented by Θ instead of a matrix. Algorithm 3 gives the procedure of HMM training in the continuous characterization of mobility features.

Algorithm 3. HMM training with continuous characterization of mobility features

Input: mobility feature matrix $\mathbf{F}$, number of Gaussian components M.
Output: HMM parameters A, Θ, and π.
Initialization:

1: Set a initial guess of A, Θ, and π.

Step 1:

2: Use the values of $\mu_{n,p,m}$, $\sigma_{n,p,m}$, and $\omega_{n,p,m}$ in Θ to obtain $\gamma_{n,p,m,t}$ by (12);

3: Update the values of $\mu_{n,p,m}$, $\sigma_{n,p,m}$, and $\omega_{n,p,m}$ in Θ according to (13)–(14);

4: Update A and π according to Step 1 and Step 2 in Algorithm 2.

Step 2:

5: Return to **Step 1** and repeat until convergence.

2.4. HMM prediction

After the HMMs are well trained according to the previous subsection, they can be used to predict the driving intention of a given vehicle. For the targeted vehicle, a historical trail of its mobility features is used to predict its driving intention in following time steps. For example, a historical trail of features may show that the targeted vehicle has been keeping driving in one lane, and this indicates either a trend of lane-change or lane-keeping behavior in the future. It is required to predict which behavior is most likely to happen.

Besides, the historical trail of features of the surrounding vehicles in the same time period may also be used together for the driving intention prediction of the targeted vehicle. In this case, the traffic environment around the target vehicle is considered. Since the surrounding vehicles close to the targeted vehicle can have an influence on the driving behaviors of the targeted vehicle, taking the mobility features of them into account can help the models to predict the driving intentions of the targeted vehicle more accurately. However, adding the trails of mobility features of some surrounding vehicles may significantly increase the number of features in the training of HMMs. With a limited maximum number of iterations, the training algorithms may not be well converged in the case of a large mobility feature matrix. As a result, the prediction accuracy may be dropped in some experiments where the algorithms are not well converged.

As described above, the historical trail of the mobility features of the targeted vehicle, or the historical trails of the mobility features of the targeted vehicle and the surrounding vehicles, can be used as the observation of the HMM. When predicting the driving intention, the observation is used as the input of the prediction algorithm. Then, the probability that the observation is produced by each HMM λ_i is calculated by Forward Algorithm [20]. After that, the HMM that is most likely to give this observation is selected, i.e.,

$$i = \arg\max_{i} P(O|\lambda_i), \tag{15}$$

Note that the trained models can be generally applied to predict different types of driving intentions of vehicles. In consideration of the items in the dataset, we set the driving intentions as lane-changing intentions in the experiment in the next section. Thus, $i \in \{1, 2, 3\}$, where $i = 1$ refers to the driving intention of changing to the left lane, $i = 2$ refers to the driving intention of changing to the right lane, and $i = 3$ refers to the driving intention of keeping on the original lane. The driving intention that i represents for is considered as the driving intention of the targeted vehicle.

3. Experimental results and analysis

3.1. Experiment scenario

As shown in Fig. 3(a), the experiment is implemented with the traffic data of the vehicles collected on the JianGuoMen Flyover in Beijing in 2017. It is a three-layer interconnected overpass, usually with high traffic density and complicated traffic conditions. Given a dataset of historical locations of the vehicles in a period of time on the flyover, the proposed method in this paper is used to predict the driving intentions of the vehicles. To demonstrate the scenario, the dataset is imported into ArcMap and Fig. 3(b) is plotted. Each dot is a node on the flyover and the location coordinate of it is available. Each gray line is the central axis of the road segment. The red nodes make up a selected main road on the flyover, which is a two-way road with seven lanes. The path history data of 3910 vehicles on this selected road is collected. The triangles of four different colors represent the trails of four vehicles on this road, and the time when each location is recorded is also shown in the figure. In this paper, the driving intentions on this road are divided into three types, i.e., changing to the left lane, changing to the right lane, and keeping on the original lane. 60% of the 3910 pieces of data are used to train the model, while 40% of them are used as a test set which gives a prediction accuracy. The prediction accuracy is used as criteria for evaluating the performances of the proposed method.

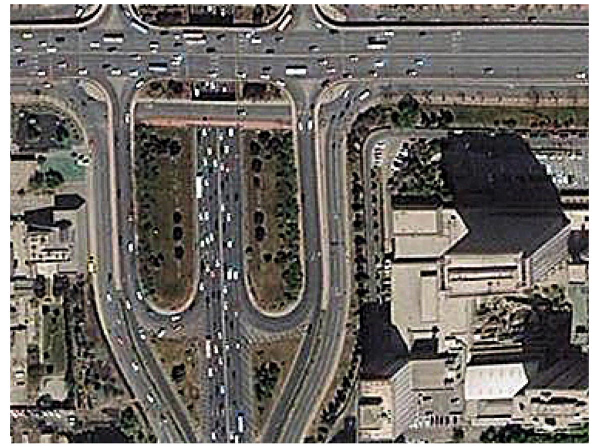
In this section, the performances of the proposed driving intention prediction method are evaluated under different conditions. In the experiment, a trail of features of a vehicle is truncated into a sequence of 9 time steps, i.e., $T = 9$. Since each time step is a time period of 0.5 s, a trail lasts for 4.5 s. A vehicle may keep in one lane or change lanes in the 4.5 s. For the convenience of classification, when truncating the mobility data of the vehicles, it is ensured that the lane-changing vehicles complete the lane-change behavior (i.e., move across the lane line) at the last time step of the trail. In addition, a vehicle only changes lane once in one trail.

As illustrated in Fig. 4(a), at each time step, the selected types of mobility features of the targeted vehicle are computed, i.e., the velocity v, the moving direction θ, and the offsets from the lane lines d_1, d_2. The example in Fig. 4(b) gives the collected raw data of a vehicle and the values of its selected mobility features. Moreover, since the driving intention of the targeted vehicle may be influenced by the movement of the surrounding vehicles, this paper further takes the trails of mobility features of the surrounding vehicles into account as well. In order to make sure that vehicles in all directions are considered, we choose one nearest surrounding vehicle (if it exists) from each of the 8 regions, instead of simply choosing a specific number of nearest vehicles. The sizes of the regions are determined by $l_1 = 4$ m, $l_2 = 6$ m, $l_3 = 1$ m and $l_4 = 1.5$ m. In particular, the values of l_1 and l_2 depend on how far away the vehicle may have an influence on the targeted vehicle, while l_3 and l_4 are related to the safe distance between vehicles. Then, the mobility features of the selected surrounding vehicles are added to the elements of the feature matrix $\mathbf{F}$.

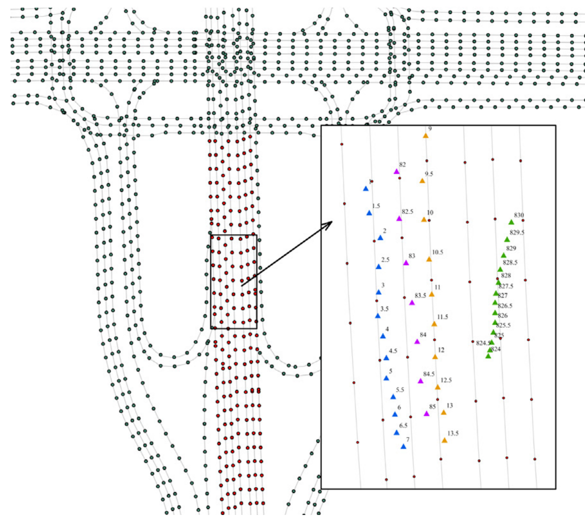
When evaluating the performance of the prediction, the prediction time refers to the interval between the time that we make the prediction and the time that the trail finishes. For example, when the prediction time equals to 3.0 s, it means that to predict the driving intention of the targeted vehicle at $t = T$, we have to make the prediction at 3 s earlier. The prediction accuracy is statistically measured. A number of vehicles are used as a test set and the driving intention of them are predicted. The accuracy equals the ratio of correct predictions.

3.2. Results and analysis

The performances of the proposed prediction method are tested with different feature characterization approaches and different parameters. Moreover, we compare our proposed method with the method based on logistic regression (LR) models [23]. An LR model is suitable for classifying samples of two categories, while three types of driving intentions are involved in this section. Thus, three LR models are trained for driving intention prediction. Each LR model is used to achieve the probability of two of the three types of driving intentions, and then the type of the driving intention with the highest probability is selected as the result of prediction. The LR models are trained with the help of MATLAB Statistic Toolbox. In Fig. 5, it is indicated that when the prediction is earlier, the prediction accuracy becomes lower, no matter which method is applied. Moreover, Fig. 5(a) shows that the proposed method gives a higher prediction accuracy then the method based on LR model. Fig. 5(a) also shows that when the discrete characterization of mobility features is applied, a larger number of clusters, i.e., K, produces a higher prediction accuracy. Fig. 5(b) shows that the continuous characterization of mobility features achieves an increased prediction accuracy, compared to the case of discrete characterization. This increase is more significant when the prediction time is larger. Moreover, in a prediction experiment of the case of discrete characterization, the program runs an average of 9.3 s. In a prediction experiment of the case of continuous characterization, the program runs an average of 37.2 s. The simulation program for the case of discrete characterization runs much faster than that for the case of continuous characterization, which means the HMMs trained with the discrete characterization of mobility features can give a faster prediction with a lower prediction accuracy.

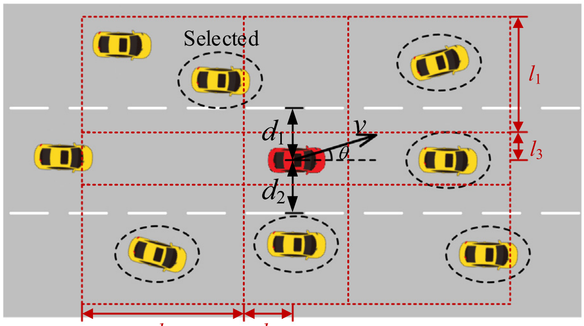


(a) JianGuoMen Flyover in Beijing.



(b) Field collected data of vehicles on the selected road.

Fig. 3. Simulation scenario: JianGuoMen Flyover and the selected road. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(a) Mobility features of the targeted vehicle and the selection of the surrounding vehicles.

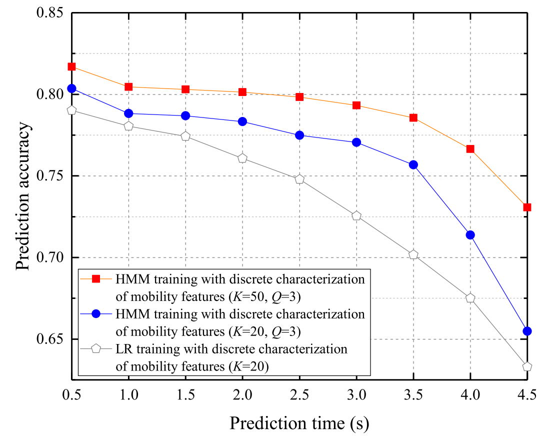
Field collected data					Mobility features			
veh_idx	time(s)	loc_x(m)	loc_y(m)	link_id	v(m/s)	θ(deg)	d_1(m)	d_2(m)
31	1.0	31248.2	-2555.62	1986	6.507718	5.290081	1.599447	-2.356589
31	1.5	31248.5	-2552.38	1987	6.766417	11.94099	1.869767	-2.086233
31	2.0	31249.2	-2549.07	1987	5.609848	-10.2683	2.219767	-1.736233
31	2.5	31248.7	-2546.31	1988	5.793824	-3.95879	2.08986	-1.865877
31	3.0	31248.5	-2543.42	1988	6.14	0	1.98986	-1.965877
31	3.5	31248.5	-2540.35	1988	6.45241	-3.55418	1.98986	-1.965877
31	4.0	31248.3	-2537.13	1989	6.033274	-3.80144	2.009663	-1.945607
31	4.5	31248.1	-2534.12	1989	7.863841	7.30576	1.909663	-2.045607
31	5.0	31248.6	-2530.22	1990	6.842923	1.674838	2.2795	-1.675659

(b) An example of the field collected data and the mobility features.

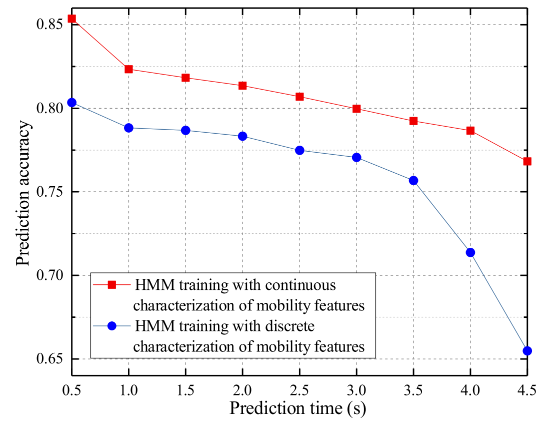
Fig. 4. Selection of mobility features.

In Fig. 5(c), when the continuous characterization of features is applied, increasing the number of Gaussian components M within a range can improve the performances of driving intention prediction. When the number of hidden states Q becomes larger, the prediction accuracy is improved as well.

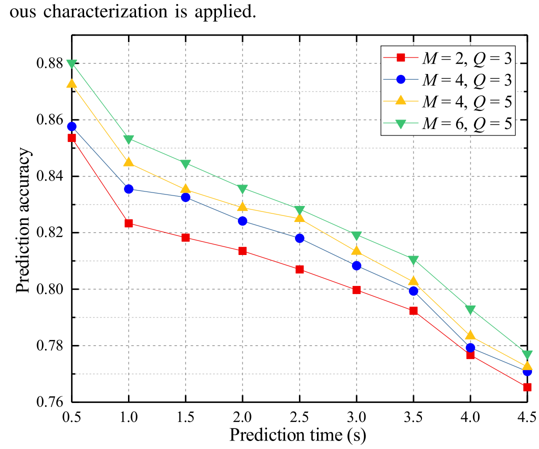
In Fig. 6, the red line with square symbols is obtained when only the mobility features of the targeted vehicle are used as the input of the feature characterization. Then, the mobility features of the surrounding vehicles are taken into account. Since the locations of the surrounding vehicles may limit the driving intention of lane-changing, the relative positions of the selected surrounding vehicles are added to the feature matrix. The relative position of a surrounding vehicle refers to the difference in location coordinates between the surrounding vehicle and the targeted vehicle. As a result, the prediction accuracy is improved when the prediction time is long. After that, since one of the reasons that a driver chooses to change lane is to get an increase in speed, we introduce the ratio of the average velocity of vehicles on the adjacent lane and that of vehicles on the current lane as a mobility features added on the basis of the previous features. The results show that the prediction accuracy is further improved. Note that when the prediction time is smaller than or equals to 1.5 s, the prediction accuracy in the case of only mobility features of the targeted vehicle involved is a little higher, compared to the cases where both the mobility features of the targeted vehicle and those of the surrounding vehicles are involved in. This is because in the latter case, the number of the features is significantly increased and the size of the mobility feature matrix is enlarged. As a result, in some experiments, Algorithm 2 or 3 may not be converged after the maximum number of iterations has been reached. The accuracy is a little lower in these experiments, and hence the average prediction accuracy in this case is dropped. Compared with a large prediction time, when the prediction time is small, it is easier to predict the driving intention of the targeted vehicle based on the current status of the targeted vehicle, so the case of only the targeted vehicle involved can have a good performance. Therefore, when the prediction time is smaller of equal to 1.5 s, the prediction accuracy of the case of only the targeted vehicle involved is higher than the prediction accuracy of the other two cases which are affected by the convergence of Algorithms. In general, the introduction of the mobility



(a) Prediction accuracy when discrete characterization is applied with different methods and different K.



(b) Prediction accuracy when discrete characterization or continuous characterization is applied.



(c) Prediction accuracy when continuous characterization is applied with different M and Q.

Fig. 5. Prediction accuracy with different methods and different parameters.

features of the surrounding vehicles can increase the accuracy of the prediction of the targeted vehicle.

Reviewing all the above experimental results, it is indicated that the performances of the proposed method are related to the parameter setting of the model, the selection of the mobility features of vehicles, as well as the applied characterization approach of mobility features.

4. Conclusion

In this paper, a driving intention prediction method in a mixed-traffic scenario is proposed based on HMM. The proposed method can

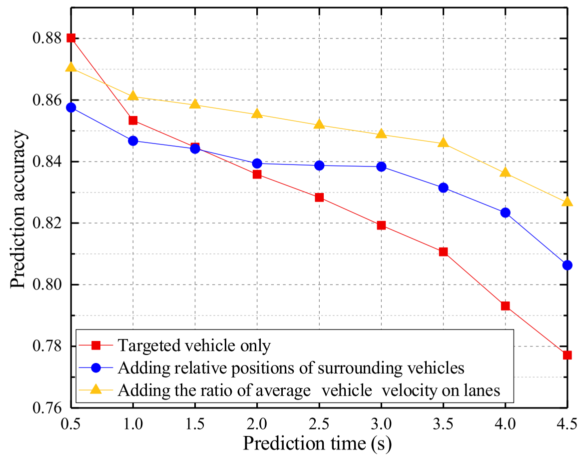


Fig. 6. Prediction accuracy with different mobility features involved.

be applied to help the autonomous vehicles to predict the driving intentions of the human-driving vehicles on the road. In the method, either discrete or continuous characterization of the mobility features is applied, and the mobility feature matrix is turned into a set of observations in HMMs. With adequate samples of observations, HMMs representing different driving intentions are trained by the training algorithms. After that, the well-trained HMMs are used to predict the driving intention of a given targeted vehicle. The HMMs are trained and tested with field collected data from a flyover. In the HMM training and prediction, either the mobility features of the targeted vehicle, or the mobility features of the targeted vehicle and the surrounding vehicles are involved in. Numerical results show that the proposed method can achieve higher prediction accuracy than the method based on LR models, and the HMMs trained with the continuous characterization of mobility features can give a higher prediction accuracy when they are used for predicting driving intentions. Adopting different parameters in the process of mobility feature characterization gives different performances in prediction. Moreover, when the surrounding vehicles are involved in the training and prediction, the influence of the surrounding traffic on the targeted vehicle is taken into account, and the performances of the prediction method are further improved.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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