Journal of Computers Vol. 30 No. 6, 2019, pp. 46-59
doi:10.3966/199115992019123006004

Vehicle Trajectory Prediction Algorithm Based on Mobility Characteristics in Vehicular Ad Hoc Networks

Lei-lei Wang[1,2], Zhi-gang Chen[1,2*], Jia Wu[1,2], Jiaqi Liu[1,2]

[1] School of Computer Science and Engineering, Central South University, Changsha 410075, China

[2] 'Mobile Health' Ministry of Education-China Mobile Joint Laboratory, Changsha 410083, China
wll_1234@163.com, czg@csu.edu.cn, jiawu5110@163.com, liujiaqi@csu.edu.cn

Received 3 January 2018; Revised 15 May 2018; Accepted 4 July 2018

Abstract. For intelligent transportation system (ITS), accurate, real-time and reliable vehicle trajectory prediction has become a hot research topic in the mobile object database. Accurate and reliable vehicle trajectory prediction can improve traffic safety and effectively promote urban road planning. Because vehicle motion is susceptible to environmental changes and user behavior, it is difficult to accurately predict its trajectory. Aiming at the low accuracy of vehicle trajectory prediction and the lack of real-time prediction, this paper proposes a new trajectory prediction method TPMC (Vehicle trajectory prediction algorithm based on mobility characteristics, TPMC). This algorithm is mainly applied to vehicle trajectory prediction under short distance. Based on the historical trajectory, the vehicle movement characteristics are analyzed, and then the appropriate vehicle movement model is designed to obtain the vehicle movement trajectory in the future. On this basis, the vehicle moving position and distance information are determined. The results of simulation indicate that the proposed method has a high prediction accuracy with less time overhead compared with other existing prediction methods.

Keywords: ITS, moving object database, vehicle movement characteristics, vehicle trajectory prediction

1 Introduction

As an important branch of wireless communication technology, vehicular ad hoc network (VANETs) [1] is a kind of wireless ad hoc network that will provide technical support for the safe, comfortable and intelligent urban traffic environment. Vehicular Ad Hoc Networks is a special mobile ad hoc network, it has its own unique network characteristics. Users in these vehicles can conveniently communicate with other vehicles via wireless communication devices [2]. Therefore, the vehicular network is widely used in traffic conditions report, vehicle collision warning, automatic pilot navigation and other transportation areas.

Driving safety is one of the most significance works for the developers of automotive industry and researchers. An accurate and reliable vehicle trajectory algorithm can improve driving safety by detecting potential collisions in advance and reducing the risk of vehicle collisions. When the alarm is reminding, there only have a limited time left for the drivers to react. Although many vehicles equipped with the warning system there still have a risk of collision.

With the earlier trajectory prediction, drivers can perceive nearby vehicle movements and traffic conditions in advance so that they have enough time to react appropriately, avoid potential dangers, and make safer and more effective driving actions. Active self-driving cars and safety systems are an ideal solution to reduce the number of traffic emergencies [3]. The advanced driver assistance systems (ADAS) like as collision warning system, adaptive cruise control and emergency braking system, that already be applied in some vehicles, can be used to warn the driver and even meddle on the state of the vehicle. If

* Corresponding Author

we can predict the vehicle trajectory accurately and in time, we can better realize the communication between vehicles and prevent the unexpected events as soon as possible. Predicting the vehicle trajectory is an uncertainly work due to it relies on each driver's behavior and intention. The prediction based on vehicle's movement model can accurately predict the trajectory of the vehicle within a short distance.

The vehicle network is applied to the urban transportation system, and its operating environment is more complex than the general self-organizing network [4]. At present, with the rapidly development of Global Positioning System (GPS) technology, mobile computing and wireless communication technology, the research of vehicle location based on vehicle navigation and other wireless devices has become a challenging hot spot. In real life, the movement of vehicles is always restricted by a lot of outside privacy, not the irregular movement. The mode of vehicle movement is mainly influenced by the following factors: the distribution of the road, the way of human behavior [5] and the classification of the vehicle, etc. The constraints of these external factors make the network node movement pattern in the vehicle network very different from the traditional self-organizing network. And these differences make the vehicle network more complex [6]. In spite of many external factors such as road conditions and human social behavior habits, the motion characteristics of the vehicle network still exist a certain regularity. Analyzing the regularity of the vehicle movement pattern and getting the correct prediction of the future vehicle movement trajectory have quite significant meanings for rapid data transmission, traffic management and human daily life.

The rapidly development of vehicular networks has brought many new applications to urban transport and provided technical support for the construction of safe and comfortable urban traffic conditions. However, most of these applications encounter performance bottlenecks in the actual running environment. Due to the vehicle speed is relatively fast, the communication time between the vehicles can be kept relatively short, which results in less data transmission. If we can predict the location and state of the vehicle in advance, such as driving speed, driving direction and road type, so we can use these information to select the optimal communication link when the communication link is selected. The predictable moving position of the vehicle in the future, which will bring great help to the performance of the upper application system of the vehicular network [7]. Based on these analysis, the prediction of the vehicle's trajectory is one of the great significance for the applications of the vehicular network. However, for many reasons, it is still a very challenging research to predict the future driving position of the vehicle. First, the road distribution in the city is complex. In such a complex environment, it is difficult to choose the driving path of the vehicle. Secondly, the destination of each vehicle may be different. Finally, the urban traffic conditions vary dynamically over time. In spite of this, there is still a certain regularity in the driving of the vehicle. The regularity of vehicle movement makes it possible to predict the future vehicle movement trajectory with a certain probability by analyzing the historical operating trajectory [8]. According to the geographical location, vehicle trajectory can be divided into two patterns: short-range prediction and long-range prediction. Due to the distance of the long-range prediction is farther than the short-range, it is difficult to achieve high prediction accuracy. The short-range prediction is used to predict the vehicle trajectory at the next moment based on the current position or the historical trajectory information, and its accuracy is higher than the long-range prediction. This article mainly focuses on vehicle trajectory prediction in short-distance situations shown as Fig. 1.

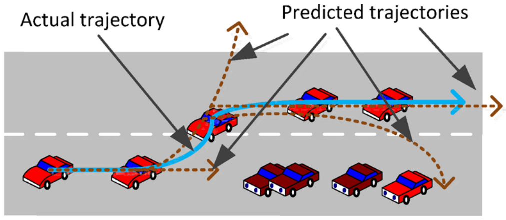

Fig. 1. Trajectory prediction

In this paper, we focus on trajectory prediction by analyzing the vehicle historical trajectory. The proposed algorithm mainly used to predict the vehicle trajectory under the short distance. The algorithm analyzes the vehicle movement characteristics according to the historical movement trajectory, and then designs a suitable vehicle movement model to obtain the vehicle movement trajectory in the future. On this basis to predict the vehicle movement and movement distance information. The advantage of the TPMC algorithm is that the vehicle can use the mobile coordination factor to select more accurate motion characteristics according to its mobile characteristics.

The main contribution of this article lies in the following aspects:

(1) Analyzing the historical trajectory (it is composed of a series of discrete historical locus points, which are mainly used to represent the location of the vehicle and the value of the driving speed) to build an appropriate model of vehicle movement characteristics.

(2) That vehicle moving model is mainly used to predict the moving speed of the vehicle at the next moment. By changing the value of vehicle mobile coordination factor, the vehicle speed at the next moment is obtained. And get the average value of all possible values as the speed of vehicle at the following time.

(3) Predicting the moving position and moving distance of the vehicle based on the predicted traveling speed of the vehicle.

The rest of this paper is structured as follows. In Section 2, we describe and analyze the related works. In Section 3, definitions and computing methods for vehicle trajectory prediction are presented. Simulation results are presented in Section 4. The last section concludes this paper.

2 Related Works

Many previous research results have shown that the mobility of vehicles has a very significant impact on the performance of the vehicle trajectory prediction [9]. At present, many researchers all over the world have studied the uncertain trajectory prediction of mobile objects, which be divided into three kinds. (1) Trajectory time segmentation query [10]. By dividing the trajectory in time, the trajectory information in a particular period of time is querying to predict the next position. (2) Based on GPS data. Zhang et al. [11] puts forward the use of GPS historical data characteristics, which recommended the best path. However, this method does not consider the impact of dynamic environment on the prediction results, and the prediction accuracy is not high. (3) Mining frequent trajectory patterns to predict the future trajectory. Uncertainty trajectory prediction method [12], which scheme divides each road into a section of different width and length, and then detects the congestion section through the saturation of the section and the average speed of the vehicle. A hierarchical road network model [13], by reducing the road network of intersection nodes, reduces complexity, improves performance, reduces the storage of data and avoids unnecessary communication overhead. On the basis of the model, a detection backtracking algorithm is proposed, which selects the highest probability road fragments according to the information of the layered road network.

Physics-based prediction is one of a common ways to predict vehicle trajectory in a short term [14,]. The article [15] researched the vehicle trajectory prediction and inspected the possible method for vehicle trajectory prediction based on the differential global positioning system. In this article, different vehicle trajectory prediction algorithm were compared and the simulation results indicated that the proposed algorithm have a higher accuracy when our prediction be ran in the short-rang case. Xie et al. [16] focused on the driver control and used the parameter to obtain better prediction. In the paper [17], the collision risk estimation is achieved through vehicle trajectory prediction and vehicle-to-vehicle communication tools. Woo et al. [4] proposed a vehicle trajectory prediction approach for lane change focusing on the high-level driving status. This approach use Hidden Markov Models (HMM) to analyze the vehicle movement based on driving habits estimation and classification. Song et al. [18] presented a filter based on the dynamic Bayesian network that could appraise the driving habits and anticipate the vehicle future trajectory. In this paper, the vehicle movement characteristics be analyzed by processed the historical trajectory information. The vehicle movement model was proposed to predict the future vehicle trajectory. Besides some time-series models using data could to predicted the trajectory such as autoregressive integrated moving average models and artificial neural networks. These models also could predict more accurately in the short-rang.

At present, a variety of prediction models have been applied to vehicle trajectory prediction, such as Bayesian network, Markov chain, hidden Markov model, mixed Markov model, Gauss process, Gauss mixture, Kalman Filter (KF) and so on. Best and Fitch [19] proposes to predict trajectories by combining Bayesian network. Compared with traditional trajectory prediction methods, the advantage of this method is to illustrate the feasibility of integration with higher level planning algorithm. In this study [20], the interactive multiple model trajectory prediction (IMMTP) method is proposed by combining the two predicting models. Ye et al. [21], considering the influence of velocity change on the prediction accuracy, a parameter adaptive selection trajectory prediction algorithm based on Hidden Markov model is proposed. The proposed trajectory prediction method [22] employs the recurrent neural network called long short-term memory (LSTM) to analyze the temporal behavior and predict the future coordinate of the surrounding vehicles. The Gauss mixture model is used to predict the trajectory probability and to deduce the joint probability distribution of the future motion by observing the historical trajectory model. In spite of this, the method only takes into account the historical trajectory, resulting in poor overall prediction results. Qiao et al. [23] studied the trajectory prediction method of Gauss hybrid model, which has high prediction accuracy. Malekian et al. [24] used Hidden Markov Models (HMM) and Radio Frequency Identification (RFID) technology to improve the performance of intelligent vehicle navigation systems. The paper [25] present a new approach to vehicle trajectory prediction based on automatically generated maps containing statistical information about the behavior of traffic participants in a given area. Chen et al. [26] studied the prediction-based target tracking in vision sensor networks and hoped to reduce the transmission energy of the vision sensor network by predicting the direction and speed of the moving target.

3 Vehicle Trajectory Prediction Algorithm Based on Mobility Characteristics

In order to provide high quality position based services, it is necessary to analyze the historical trajectory of the vehicle and predict the future trajectory. However, trajectory prediction is not only dependent on the historical trajectory alone, but also needs to consider various factors, such as roads, traffic conditions, sports environment and personal behavior habits. The regularity of human activity leads to a very strong temporal and spatial correlation in the change of traffic state. The TPMC algorithm analyzes vehicle movement characteristics through observing historical trajectory information, then designs appropriate vehicle mobility model to predict vehicle movement trajectory in the future. On this basis, the mobile location and Vehicle movement distance information of the vehicle are predicted.

3.1 Algorithmic Definition

The known vehicle moving object database *DB*, which stores a large number of moving information of vehicle at different times, the ordered set of moving information in time is called trajectory, expressed in $DB = \{Tr_1,\ Tr_2,\ldots Tr_n\}$, and the number of trajectories is defined as |*DB*|. Vehicle history trajectory sequence $Tr = \left\{s_1, s_2, \ldots s_g\right\}$ represents a sequence of ordered discrete trajectory points $\{s_i = (x_i, y_i, v_i, t_i) \mid 1 \le i \le g\}$. Where v_i represents the current position of the vehicle speed value, t_i represents the time point, $i \in [1, g), t_i < t_{i+1}$, (x_i, y_i) represents two-dimensional coordinates of moving objects.

Constructing of the required vehicle mobile model and analyzing the history of the vehicle moving object database for vehicle history data in *DB* to calculate the average vehicle moving speed. Using η to represent the average speed of vehicle for a long time movement

$$\eta = \lim_{t \to \infty} \left(\frac{\sum_{t=0}^{\infty} v_i}{t} \right) \tag{1}$$

In real life, the moving speed of the vehicle is about 40-60 km / h, it can be assumed that the moving speed of the vehicle satisfies the Gaussian distribution. According to the moving speed of the vehicle in the historical trajectory sequence, the random moving process of the vehicle in the infinite moving state under the current data is analyzed. Use ζ_n to denote vehicles' random and independent processes when the vehicles move at infinity.

$$\zeta_n = \frac{1}{\theta * \sqrt{2\pi}} e^{-\frac{n^2}{2*\theta^2}} \tag{2}$$

In the above formula, θ is the vehicle movement coordination factor, satisfies $0 \le \theta \le 1$. When $0 < \theta < 1$, indicates that the vehicle is moving completely random. At this point a completely random speed value is obtained. If $\theta = 0/1$, the vehicle move at a uniform speed. The magnitude of θ represents the mutation of vehicle speed in a short time, and it is a specific performance of the vehicle itself mobility performance.

Thus, the vehicle movement model can be defined as shown in formula (3). That is, at time $t+\Delta t$, the moving speed $v_{t+\Delta t}$ of the vehicle is calculated as:

$$v_{t+\Delta t} = ((\theta - 1)v_t + (1-\theta)\eta + \sqrt{1-\theta^2}\zeta_n)\Delta t \tag{3}$$

At $t+\Delta t$ moment, vehicle speed $v_{t+\Delta t}$ is obtained by moving characteristics and coordinating factors. However, only relying on a solely velocity value cannot achieve a relatively high and stable prediction accuracy for the vehicle trajectory prediction. And different values of the movement coordination factors will also have an impact on the value of the movement velocity at the next moment.

How to obtain a more reasonable and accurate moving speed value has a great influence on the accuracy of the prediction of the vehicle trajectory. In real life, the speed of vehicles on the road is within a certain range, and the speed is generally in the majority of 40~60km/h. Therefore, it can be assumed that the vehicle speed satisfies the Gauss distribution. Therefore, we can use the joint density probability function to obtain more accurate vehicle speed by building multiple Gauss processes.

Changing the mobile coordination factor θ ($\theta^{(i)} \in \{0,...j,k,...\gamma\}$), γ is used to represent the possible value of $\theta^{(i)}$, which satisfies $0 \le \gamma \le 1$. So at $t+\Delta t$ time, the range of vehicle speed can be expressed in $v_{t+\Delta t} \in \{v^{(1)},...v^{(m)}\}$. Establish a joint distribution function, dealing with two training data sets $\theta^{(i)} \in \{0,...j,k,...\gamma\}$ and $v_{t+\Delta t} \in \{v^{(1)},...v^{(m)}\}$.

Due to the value of the random variable $\theta^{(i)}$ only depends on the integral of the probability density function, so the probability density function at individual points does not affect the performance of random variables. Therefore, in order to obtain a more accurate vehicle traveling speed and improve the algorithm TPVN prediction accuracy, the joint density probability function can be established by constructing a plurality of Gaussian processes to obtain the probability value of the vehicle traveling speed. Based on the prediction speed value, the moving position and he moving distance of the vehicle are predicted.

Given the training data sets $\theta^{(i)} \in \{0,...j,k,...\gamma\}$ and $v_{t+\Delta t} \in \{v^{(1)},...v^{(m)}\}$, a joint density probability function of the training data set is constructed. Therefore, we construct the model that $v^{(i)}$ is generated by $\theta^{(i)}$, and the value of $\theta^{(i)}$ is randomly selected from $\{0,...j,k,...\gamma\}$. Then $v^{(i)}$ obeys one of γ Gaussian processes that depend on $\theta^{(i)}$.

$$p(v^{(i)}|\theta^{(i)}) = \textstyle\sum_{k=0}^{\gamma} \sigma_k \omega(v^{(i)},\theta^{(i)} \mid \xi_k, \Sigma_k) \tag{4}$$

Here, we define θ satisfy multiple distributions, that is $\theta^{(i)} \sim Multinomial(\sigma)$ and σ_k is a coefficient, satisfying $\sigma_k \ge 0$ and $\sum_{k=0}^{\gamma} \sigma_k = 1$, ξ_k is the center of this density function, Σ_k is variance.

It is necessary to accurately estimate the model parameters $\sigma_k, \xi_k, \Sigma_k$ by using the Gaussian process to solve the speed of probability. One of the most commonly used methods of parameter estimation is expectation-maximization (EM). The EM algorithm improves model parameter estimation in iterations, the matching probability of the model estimation parameter $\sigma_k, \xi_k, \Sigma_k$ and the observation training data set is continuously increased in each iteration. That is, equation (5) reaches $p(v^{(i)} \mid \theta^{(i)} = k) > p(v^{(i)} \mid \theta^{(i)} = j)$ for each iteration. Through continuous iteration, get the best matching training speed value. The purpose of iterative training is to find a best value of moving speed, making $p(v^{(i)} \mid \theta^{(i)})$ maximum, which is $v_{t+\Delta t} = \arg\max_{v^{(i)}} p(v^{(i)} \mid \theta^{(i)})$.

The variable $\theta^{(i)}$ means to which one of γ Gaussian processes each $v^{(i)}$ comes from. Using the likelihood function to estimate the parameter $\sigma_k, \xi_k, \Sigma_k$:

$$\ell(\sigma,\xi,\Sigma) = \sum_{i=1}^{m} \log p(v^{(i)} \mid \theta^{(i)}, \xi, \Sigma) + \log p(\theta^{(i)}, \sigma) \tag{5}$$

However, during the actual vehicle movement, θ as a mobile coordination factor is a concrete manifestation of the change of the vehicle's own performance. The change of the specific value is unpredictable. Here we will use the EM algorithm to optimize the parameters. The EM algorithm is divided into two steps. In *E- step*, the algorithm tries to guess the value of $\theta^{(i)}$. In *M- step*, parameters are updated according to the value of *E- step* guess. EM algorithm to solve Gaussian process optimization, fitting parameters $\sigma,\xi,\sum$.

E-step: for each *i* and *k* set:

$$p(v^{(i)} \mid \theta^{(i)} = k) = \frac{p(v^{(i)},\theta^{(i)})}{p(\theta^{(i)})} \tag{6}$$

M-step: Using maximum expectation method to obtain iterative estimation formula of Gauss process parameter $\sigma,\xi,\sum$. That is, the update rule of parameter $\sigma,\xi,\sum$.

$$\sigma_k = \frac{1}{m}\sum_{i=1}^{m} p(v^{(i)} \mid \theta^{(i)} = k),\ \xi_k = \sigma_k v^{(i)},\ \Sigma_k = \xi_k (v^{(i)} - \xi_k)(v^{(i)} - \xi_k)^T \tag{7}$$

E-step is assumed to know the parameters of each Gauss process, and then estimate the weights of each Gauss model. *M-step* is based on the estimated weights and then goes back to determine the parameters of the Gauss process. Repeating the above two steps until the fluctuations are small and approximate to extreme values.

The advantage of the model based on Gauss process is that the model parameters can be adaptively obtained according to different historical trajectory data. The main problem lies in: the model itself is non parametric (no need to set parameters) to solve, resulting in the amount of calculation increases with the increase of data. In the model training, the parameters are obtained by optimizing the likelihood function.

3.2 Vehicle Movement Distance Prediction

The moving distance of the vehicle means the length of the vehicle moves from moment *t* to moment $t+\Delta t$, which can be denoted by ΔDIS. Since the movement of the vehicle in a short period of time approximates a uniform motion with the average speed of the initial velocity and the final velocity, the distance of the vehicle moving at $t+\Delta t$ moment can be expressed by the displacement formula of the physics:

$$\Delta DIS = DIS_{t+\Delta t} - DIS_t = \left(\frac{v_{t+\Delta t} + v_t}{2}\right) \times \Delta t \tag{8}$$

Where DIS_t represents the total moving distance of vehicle in *t* time. The $DIS_{t+\Delta t}$ represents the total moving distance of vehicle in $t+\Delta t$ time. Expressing $v_{t+\Delta t}$ in formula (3) and integrate both sides of formula (8):

$$DIS_{t+\Delta t} = DIS_t + \frac{1}{4} \times \left[\theta(v_{t+\Delta t} + v_t) + (1-\theta)(\eta_{t+\Delta t} + \eta_t) + \sqrt{1-\theta^2}(\zeta_{t+\Delta t} + \zeta_t)\right]\Delta t^2 \tag{9}$$

3.3 Vehicle Movement Position Prediction

In real life, vehicle movement cannot deviate from the driving lane, so the next moment, the coordinate of vehicle moving position can be obtained by vehicle coordinate position at *t* moment (through historical trajectory query), vehicle moving distance and vehicle moving velocity vector angle.

If the location of the vehicle at time t can be identified by coordinates $L_t(x_t, y_t)$, so at time $t+\Delta t$, the geographic location of the vehicle can be predicted based on the vehicle position $L_t(x_t, y_t)$, speed v_t, speed $v_{t+\Delta t}$ and direction DI_t (speed vector change angle) at time *t*.

If at Δt moment, the vehicle driving direction has not changed, then the following formula approximately holds:

$$(x_{t+\Delta t}, y_{t+\Delta t}) = \begin{cases} x_{t+\Delta t} = x_t + (\dfrac{v_{t+\Delta t} + v_t}{2})\Delta t \\ y_{t+\Delta t} = y_t + (\dfrac{v_{t+\Delta t} + v_t}{2})\Delta t \end{cases} \quad \textbf{(10)}$$

If at Δt moment, the vehicle driving direction has changed, then the following formula approximately holds:

$$(x_{t+\Delta t}, y_{t+\Delta t}) = \begin{cases} x_{t+\Delta t} = x_t + (\dfrac{v_{t+\Delta t} + v_t}{2})\Delta t \cos DI_t \\ y_{t+\Delta t} = y_t + (\dfrac{v_{t+\Delta t} + v_t}{2})\Delta t \,\mathrm{sins}\, DI_t \end{cases} \quad \textbf{(11)}$$

3.4 Trajectory Prediction Error

The test data is input into the test model to get the predicted output trajectory, in which the output trajectory is a set of a series of trajectory points, and the predicted trajectory points are shown by the dashed line of the Fig. 2.

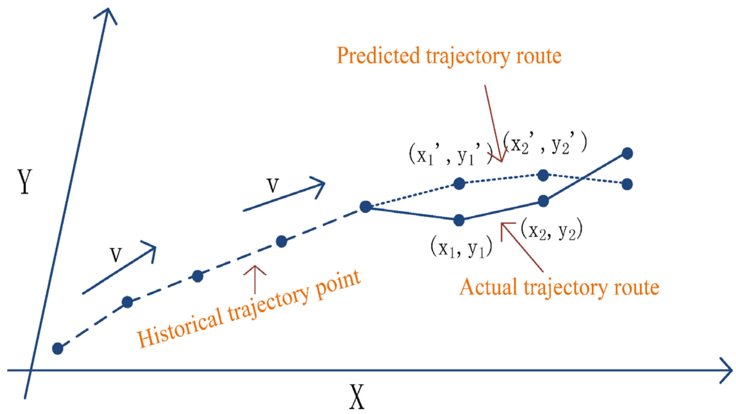

Fig. 2. An example of predicted trajectories

The Root Mean Square Error (RMSE) [27] is used to calculate the geometrical space error between the measured and the predicted position, that is, the geometric space error between the predicted trajectory point and the actual trajectory point is calculated by using the root mean square error.

$$RMSE = \frac{\sum_{k=1}^{m} \sqrt{(x_k^{'} - x_k)^2 + (y_k^{'} - y_k)^2}}{m} \quad \textbf{(12)}$$

Where (x_k, y_k) is the real trajectory position, $(x_k^{'}, y_k^{'})$ is the predicted trajectory position, and *m* is the number of predicted trajectory points.

3.5 Algorithm Design

```
Algorithm TPMC
1: Input: vehicle moving object database DB: DB = {Tr1, Tr2,...Trn};
2: Output: vehicle prediction trajectory;
3: η: the average speed of vehicle since long time movement;
4: ζn : vehicles' random and independent processes when the vehicles
   move at infinity;
```

5: θ : the mobile coordination factor;
6: σ_k ; a coefficient, satisfying $\sigma_k \geq 0$ and $\sum_{k=0}^{\gamma} \sigma_k = 1$;
7: ξ_k : the center of the joint density function;
8: $\sum_k$: the variance;
9: the moving speed $v_{t+\Delta t}$ of the vehicle:
$v_{t+\Delta t} = ((\theta - 1) * v_t + (1-\theta) * \eta + \sqrt{1-\theta^2} * \zeta_n) * \Delta t$;
10: change the mobile coordination factor θ ($\theta^{(i)} \in \{0, \ldots j, k, \ldots \gamma\}$);
11: the predicted range of vehicle movement speed $v_{t+\Delta t} \in \{v^{(1)}, \ldots v^{(m)}\}$;
12: construct a joint density probability function:
$p(v^{(i)} | \theta^{(i)}) = \sum_{k=0}^{\gamma} \sigma_k * \omega(v^{(i)}, \theta^{(i)} | \xi_k, \Sigma_k)$.
13: use the likelihood function to estimate the parameter $\sigma_k, \xi_k, \Sigma_k$:
$$\ell(\sigma, \xi, \Sigma) = \sum_{i=1}^{m} \log p(v^{(i)} | \theta^{(i)}, \xi, \Sigma) + \log p(\theta^{(i)}, \sigma)$$
14: the EM algorithm optimize the parameters:
$$\sigma_k = \frac{1}{m} \sum_{i=1}^{m} p(v^{(i)} | \theta^{(i)} = k),\ \xi_k = \sigma_k * v^{(i)},\ \Sigma_k = \xi_k * (v^{(i)} - \xi_k)(v^{(i)} - \xi_k)^T$$
15: get the speed of the next moment.
16: the distance of the vehicle moving at $t + \Delta t$ moment: Eq(8);
17: the vehicle position:
18: if the vehicle driving direction has not changed:
Eq(10);
19: else:
Eq(11);
20: the trajectory prediction error: RMSE(Eq(12));
21: vehicle prediction trajectory;

3.6 Algorithm Complexity Analysis

The complexity of the algorithm, that is, the resources needed when the algorithm is written into executable programs, and the resources include time resources and memory resources. The same problem can be solved by different algorithms, and the quality of an algorithm will affect the efficiency of the algorithm and even the program. The purpose of algorithm analysis is to choose the appropriate algorithm and improve algorithm. The evaluation of an algorithm is mainly considered from the time complexity and space complexity. Table 1 is a comparison of the complexity of the TPMC algorithm and the other four vehicle trajectory prediction algorithms.

Table 1. Complexity analysis of the algorithm

Algorithm	Average situation	Best situation	Worst situation	Auxiliary space
TPMC	O(nlogn)	O(n)	O(nlogn)	O(n)
PutMode	O(n^2)	O(n^2)	O(n^2)	O(n)
Naïve	O(nlogn)~O(n^2)	O(nlogn)	O(n^2)	O(n)
EAVTP	O(m+nlogn)	O(m+nlogn)	O(n^2)	O(n)
DHMTP	O(nlogn)	O(nlogn)	O(n^2)	O(n)

4 Simulation

We implement the proposed algorithm TPMC in the Opportunistic Network Environment simulator (ONE) [28] simulator. And evaluate the performance of TPMC by comparison with PutMode prediction algorithm based on time continuous Bayesian network and Naïve prediction algorithm based on HMM without adaptive parameters selection. At the same time, the influence of different mobile coordination factors on the prediction accuracy of the algorithm is also analyzed. The experimental data mainly come from the data of *MIT* parking lots, and 40453 real track data are collected, which can be downloaded by MIT Trajsingle [29].

The effect of different values of coordination factors on the performance of the algorithm is introduced. In order to explain the performance of TPMC in this paper, *RMSE* is used to calculate the prediction error. The PutMode trajectory prediction algorithm based on time-continuous Bayesian network and the Naïve algorithm based on adaptive selection of HMM without consideration of parameters, are used to compare TPMC prediction error and prediction time.

4.1 Effect of Mobile Coordination Factor on Algorithm Performance

In the simulation experiment, we only consider the situation of $0<\theta<1$. When $0<\theta<1$ indicates that the vehicle is moving completely randomly. The magnitude of the movement coordination factor value represents the sudden change of the velocity value of the vehicle in a short period of time and is a concrete manifestation of the movement performance of the vehicle itself. As shown in Fig. 3, with the value of θ increases, the prediction accuracy of the speed value at the next moment becomes higher and higher. When $0<\theta<0.75$, the prediction accuracy increases. When $0.75<\theta<1$, the predictive accuracy value shows a slow downward trend, and relatively stable. This is because the larger the value of the mobility coordination factor, the stronger the mobility of the vehicle itself, and the more time it takes to adapt to the mobility performance, resulting in a lower prediction accuracy for the next time under the current value of the mobility coordination factor.

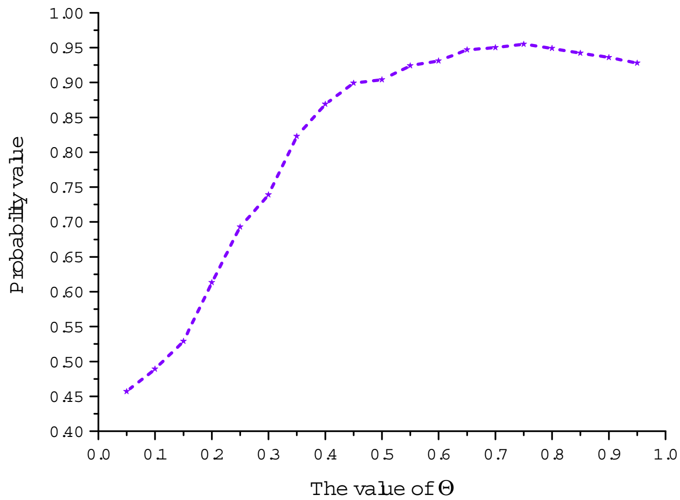

Fig. 3. Prediction Accuracy vs. value of θ

The number of verification test trajectories is from 1 to 1000, and θ takes a fixed value (0.35, 0.55, 0.75) to predict the prediction accuracy of speed value at the next moment. As shown in Fig. 4, θ takes a fixed value, and as the number of test tracks increases, the accuracy value also changes constantly, and shows an unstable trend. This is because, θ takes a fixed value can get the speed value is a fixed value, this simple speed value prediction is difficult to guarantee a relatively stable accuracy value.

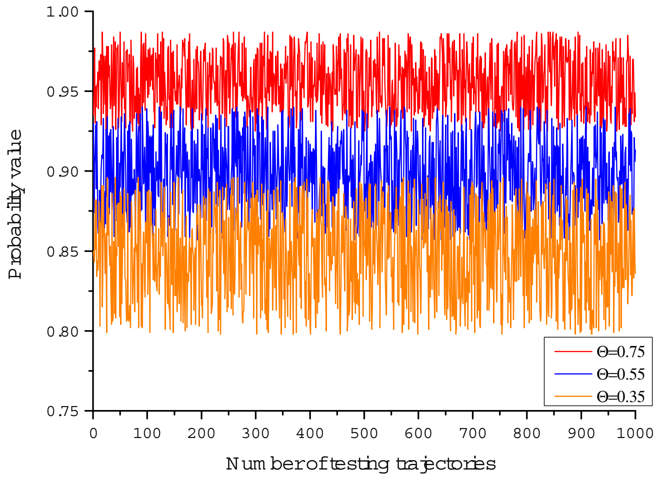

Fig. 4. Prediction accuracy vs. value of θ (0.35, 0.55, 0.75)

4.2 Prediction Error Comparison

Since the moving speed of a moving object varies randomly in practical applications, the trajectory interval size is different. In this paper, the trajectory prediction algorithm TPMC based on the moving characteristics is proposed. The results of different algorithms are compared under the random change of the moving object speed.

The prediction error can be found by comparing the various algorithms in the number of 1~1000 test trajectories as shown in Fig. 5. Compared with Naïve and PutMode algorithms, the TPMC model has a higher predictive accuracy for trajectory prediction on different test trajectory sets, with the average 36.3% higher than Naïve algorithm and 24.8% higher than PutMode algorithm. As can be seen from the Fig. 5, with the number of test trajectories increases, the prediction accuracy of TPMC is relatively higher and the *RMSE* error remains below 55m. Due to the PutMode algorithm uses the center of the trajectory of the uncertainty trajectory to represent the prediction point, the accuracy of position prediction is low, and a large prediction error occurs. The constant invariance of Naïve algorithm to parameters makes the algorithm unable to adapt to different move modes. On the contrary, the TPMC model improves the shortcoming that the moving object cannot flexibly respond to the random change of speed. By analyzing the moving characteristics of the vehicle, the dynamic state of the input trajectory and the velocity characteristics of the moving object are analyzed. The moving coordination factor be adjusted before each prediction. When faced with different trajectory data, the prediction accuracy of Naïve and PutMode algorithms is not stable. The TPMC model is relatively stable and the accuracy rate is maintained at a high level, mainly because it can adaptively select parameters for different data and better adapt to historical trajectory data.

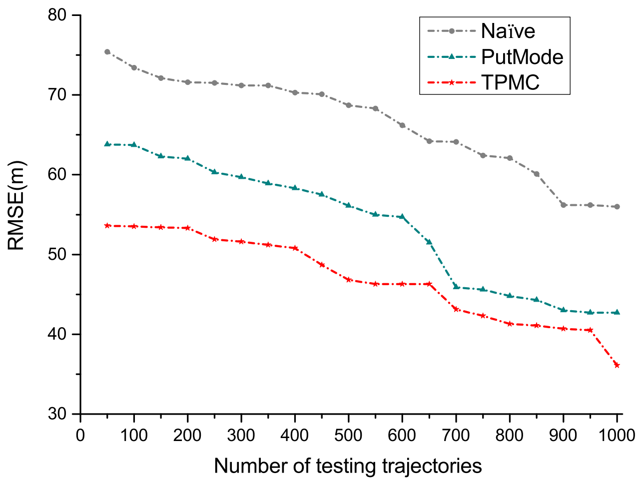

Fig. 5. Prediction error comparison under different number of testing trajectories

As shown in Fig. 6, the change of prediction error of the three algorithms over time is verified under the same test trajectories (1000). The simulation result shows that the *RMSE* errors of TPMC, PutMode and Naïve algorithm are kept at 45m, 58m and 67m on average. Simulation shows that on the same dataset, although the *RMSE* prediction error of TPMC and PutMode are very similar, the accuracy of TPMC trajectory prediction is obviously better than the PutMode and Naïve algorithm with the prediction time becomes longer. This is because the TPMC algorithm designs the moving characteristics of the vehicle under different movement coordination factors, which makes the algorithm have a good adaptability. The TPMC algorithm has a high prediction accurate than the PutMode algorithm which predicts the moving position by using the uncertain trajectory and the Naïve algorithm which is based on the HMM and has no environmental adaptation parameter.

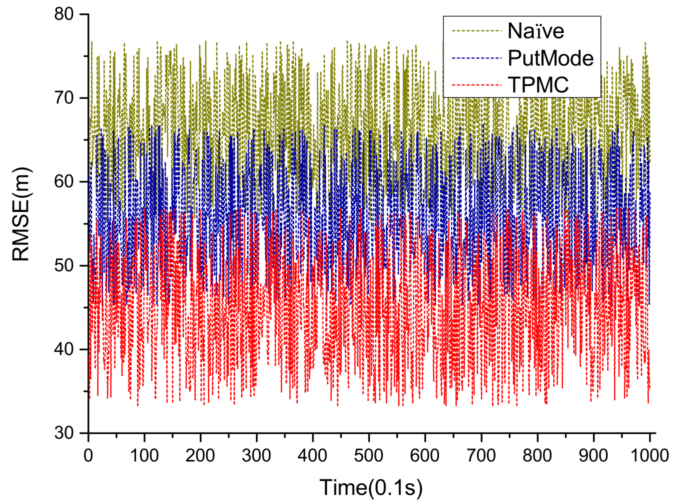

Fig. 6. Prediction error comparison under different prediction time

4.3 Prediction Time Comparison

In real-time prediction system, the prediction time of trajectory prediction model is also very important for the performance of the algorithm. In order to verify the prediction efficiency of trajectory prediction algorithm, we choose 1000 test trajectory data to do experiments. This section compares the runtime performance of the three algorithms, as shown in Fig. 7.

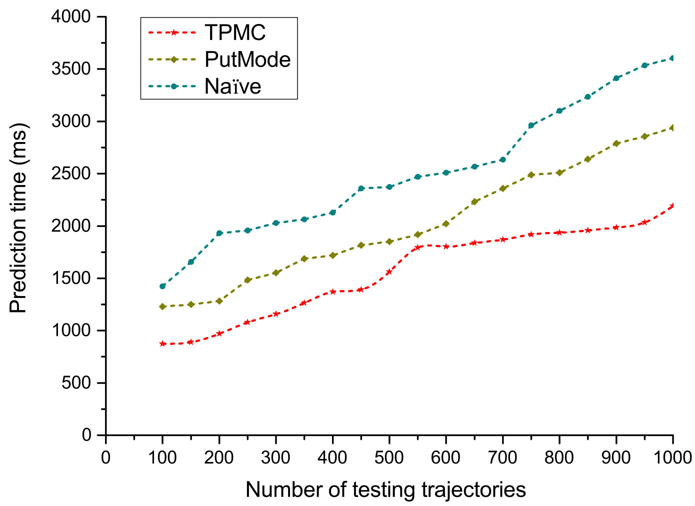

Fig. 7. Prediction time comparison

The simulation results show that the PutMode algorithm is slightly better than the Naïve algorithm. Compared with the PutMode algorithm, the TPMC algorithm has a lower prediction time, and the prediction time increases with the increase of the test trajectory data and maintains a linear relationship.

When the number of training trajectories is 1000, the prediction time is 2.3S. The prediction time of Naïve algorithm is increased compared with the TPMC algorithm, anyway the total consumption is kept in the acceptable range, and the prediction time varies linearly with the number of test trajectories. In order to show the characteristics of the algorithm, the data under extreme circumstances are tested, and the speed of the moving object is relatively slow in the real case. In other words, the TPMC model has a low frequency of parameter change, so the time cost is relatively small. Compared with the PutMode algorithm, the operation time is reduced by 8.9%. The reason is that PutMode algorithm needs a lot of time to build a continuous Bayesian network to predict, and in addition, its trajectory clustering operation costs much time and is not suitable for location big data prediction.

5 Conclusion

In this article, we proposed a new trajectory prediction algorithm (TPMC) based on vehicle motion characteristics to predict future vehicle trajectories under the short distance using the driving data from the widely studied *MITtrajsingle* dataset. This proposed algorithm was shown to achieve better prediction accuracy than the others algorithm with the RMSE error. The simulation results show the TPMC model has higher predictive accuracy averaging 36.3% higher than Naïve algorithm and 24.8% higher than PutMode algorithm and the prediction time is reduced by 8.9% and 10.5% compared with the PutMode and Naïve algorithm. Contrary to many previous studies which analyzed the vehicle movement characteristics according to the historical movement trajectory and the mobile coordination factor regulated vehicle movement to make it more stable. Although this research is highly preliminary and some limitations-not suitable for long distance prediction-should be addressed, we believe that these results constitute a promising basis to compute probable trajectories for surrounding vehicles.

The future research work focuses on three aspects:

(1) Considering the impact of objective factors on trajectory prediction, such as traffic lights, passers-by movement, traffic jams, etc.

(2) In order to improve the adaptability of the algorithm to environmental factors;

(3) Cooperating with the transport department to obtain more accurate and real-time trajectory data.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (Grant No. 71633006, Grant No. 61672540, Grant No. 61379057). This work is supported by the China Postdoctoral Science Foundation funded project (Grant No. 2017M612586). This work is supported by the Postdoctoral Science Foundation of Central South University (Grant No. 185684). Also, this work was supported partially by “Mobile Health” Ministry of Education - China Mobile Joint Laboratory.

References

[1] F. Chen, X. Bi, R. Lyu, Z. Hua, Y. Liu, Xiaoting Zhang, Adaptive virtual RSU scheduling for scalable coverage under bidirectional vehicle traffic flow, Algorithms 10(3)(2017) 1-19.

[2] L. Wang, Z. Chen, J. Wu, An opportunistic routing for data forwarding based on vehicle mobility association in vehicular ad hoc networks, Information 8(4)(2017) 1-18.

[3] V. Krishnamoorthy, S. Agarwal, KS. Venkatesh, Vehicle trajectory prediction using a catadioptric omnidirectional camera, in: Proc. International Conference on Advances in Computing, Communications and Informatics, 2016.

[4] H. Woo, J.I. Yonghoon, H. Kono, Lane-change detection based on vehicle-trajectory prediction, IEEE Robotics and Automation Letters 2(2) 1109-1116.

[5] J. Wu, Z. Chen, Human activity optimal cooperation objects selection routing scheme in opportunistic networks communication, Wireless Personal Communications 95(3)(2017) 3357-3375. DOI:10.1007/s11277.

[6] S. Chen, R. Chen, J. Gao, A monarch butterfly optimization for the dynamic vehicle routing problem, Algorithms 10(3)(2017) 107.

[7] Z. Xia, Z. Hu, J. Luo, UPTP vehicle trajectory prediction based on user preference under complexity environment, Wireless Personal Communications 97(3)(2017) 4651-4665.

[8] R. Zhang, L. Cao, S. Bao, A method for connected vehicle trajectory prediction and collision warning algorithm based on V2V communication, International Journal of Crashworthiness 22(1)(2017) 15-25.

[9] F. Wu, K. Fu, Y. Wang, A spatial-temporal-semantic neural network algorithm for location prediction on moving objects, Algorithms 10(2)(2017) 37.

[10] F. Liu, M. He, Y. Liu, Trajectory prediction based on the notion of time and the influence of location of historical time step, in: Proc. International Conference on Communications, Information Management and Network Security, 2016.

[11] Y. Zhang, S. Guo, K. Xing, Mining algorithm of spatial-temporal co-occurrence pattern based on vehicle GPS trajectory, in: Proc. IEEE International Conference on Signal and Image Processing, 2017.

[12] K.S. Bok, H. Li, J.T. Lim, Discovering congested routes using vehicle trajectories in road networks, Advances in Multimedia 2015(1)(2015) Article ID 420689.

[13] H. Huo, S.Y. Chen, B. Xu, A Trajectory Prediction Method for Location-Based Services, APWeb Workshops, 2015.

[14] C. Barrios, Y. Motai, D. Huston, Trajectory estimations using smartphones, IEEE Transactions on Industrial Electronics 62(12)(2015) 7901-7910.

[15] P. Wang, J. Wang, C.Y. Chan, Trajectory prediction for turning vehicles at intersections by fusing vehicle dynamics and driver's future input estimation, Transportation Research Record Journal of the Transportation Research Board 2602(2016) 68-77.

[16] G. Xie, H. Gao, L. Qian, Vehicle trajectory prediction by integrating physics-and maneuver-based approaches using interactive multiple models, IEEE Transactions on Industrial Electronics 65(7)(2018) 5999-6008.

[17] Y. Wang, J. Shen, X. Liu, Dynamic obstacles trajectory prediction and collision avoidance of USV, in: Proc. IEEE Control Conference, 2017.

[18] Y. Song, G. He, D. Yu, Modified Bayesian inference for trajectory prediction of network virtual identity based on spar, in: Proc. International Conference on Intelligent Human-Machine Systems and Cybernetics, 2016.

[19] G. Best, R. Fitch, Bayesian intention inference for trajectory prediction with an unknown goal destination, in: Proc. IEEE International Conference on Intelligent Robots and Systems, 2015.

[20] G. Xie, H. Gao, L. Qian,, Vehicle trajectory prediction by integrating physics- and maneuver-based approaches using interactive multiple models, IEEE Transactions on Industrial Electronics 65(7)(2018) 5999-6008.

[21] N. Ye, Y. Zhang, R. Wang, Vehicle trajectory prediction based on hidden Markov model, KSII Transactions on Internet & Information Systems 10(7)(2016) 3150-3170 .

[22] B.D. Kim, C.M. Kang, S.H. Lee, Probabilistic vehicle trajectory prediction over occupancy grid map via recurrent neural network, in: Proc. International Conference on Intelligent Transportation, 2017.

[23] S.J. Qiao, K. Jin, H. Nan, Trajectory prediction algorithm based on Gaussian mixture model, Journal of Software 26(5)(2015) 1048-1063.

[24] R. Malekian, A.-F. Kavish, B.T. Maharaj, P.K. Gupta, G. Singh, H. Waschefort, .Smart vehicle navigation system using hidden Markov model and RFID technology, Wireless Personal Communication 90(2016) 1717-1742.

[25] J. Quehl, H. Hu, S. Wirges, An approach to vehicle trajectory prediction using automatically generated traffic maps, in:

Proc. 2018 IEEE Intelligent Vehicles Symposium, 2018.

[26] T.-S. Chen, , H.-W. Tsai, J.-J. Peng, .Prediction-based object tracking in visual sensor networks, Wireless Personal Communication 87(2016) 145-163.

[27] R. Zhang, L. Cao, S. Bao, A method for connected vehicle trajectory prediction and collision warning algorithm based on V2V communication, International Journal of Crashworthiness 22(1)(2017) 15-25.

[28] A. Keränen, J. Ott, T. Kärkkäinen, The ONE simulator for DTN protocol evaluation, in: Proc. 2nd International Conference on Simulation Tools and Techniques, 2009.

[29] X. Wang, K.T. Ma, G. Ng, E. Grimson, Trajectory analysis and semantic region modeling using a nonparametric Bayesian model, in: Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 2008.