HMM-Based Traffic State Prediction and Adaptive Routing Method in VANETs

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Abstract. As the number of vehicles increases, the traffic environment becomes more complicated. It is important to find a routing method for different scenarios in the vehicular ad hoc networks (VANETs). Although there are many routing methods, they rarely consider multiple road traffic states. In this paper, we propose a traffic state prediction method based on Hidden Markov Model (HMM), and then choose different routing methods according to different traffic states. Since we are aware that GPS may cause measurement errors, Kalman Filter is used to estimate the observation, which makes observation more accurate. For different road states, we can make appropriate methods to improve routing performance. When the road is in rush hour, we will use Extended Kalman Filter to predict vehicle information in a short time to reduce the number of broadcasts, which can alleviate channel load. The result show that our method is useful for reducing the number of packets and improving the delivery rate.

Keywords: VANETs · Kalman filter · HMM · Traffic state prediction

1 Introduction

With the rapid development of communication technologies, VANETs have become an important component of the Intelligent Transportation System (ITS) and played a very important role in many fields. The purpose of ITS is to provide reliable traffic management and make more coordinated, safer, and optimal use of transport networks. VANETs, an extension of MANETs, can be used to improve traffic management and reduce traffic accidents [1,2].

In recent years, with the increasing number of vehicular nodes, dealing with traffic congestion characterized by longer trip times, slower speeds, and complex

Supported by National Natural Science Foundation of China with grant number [61701162].

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H. Gao et al. (Eds.): CollaborateCom 2020, LNICST 350, pp. 236–252, 2021.
https://doi.org/10.1007/978-3-030-67540-0_14

traffic environment have been an important issue. Thus, V2V communication plays an important role to reduce traffic congestion by exchanging road information among vehicles.

In VANETs, in order to better establish V2V communication, routing algorithm are divided into two types, position-based and topology-based [3]. Topology-based routing schemes generally require additional node topology information during the path selection process [4]. Geographic routing uses neighboring location information to perform the packet forwarding. The traditional position-based routing is Greedy Perimeter Stateless Routing (GPSR) [5]. In GPSR, the node used the information about the router's immediate neighbors to make greedy forwarding decision. However, GPSR may have unstable nodes and destroy network connectivity. Togou et al. [6] presented a distributed routing protocol, which computes end-to-end for the entire routing path and builds a stable route. In addition to information based on the location of vehicles on the road, some traffic information is also used in routing optimization methods. Vehicles can choose the best route to their destination based on real-time traffic information [7].

Because the vehicle moves at high speed on the road and changes direction frequently, which will cause communication link disconnection and information loss, some predictive routing methods and auxiliary methods have been proposed. Reza et al. [8] proposed a position prediction based multicast routing, which can alleviating the broadcast storm problem of multicast tree discovery and simultaneously minimizing the number of forwarding vehicles. The probability prediction-based reliable and efficient opportunistic routing algorithm is proposed [9]. Liu et al. [10] used Kalman Filter to predict the location of the vehicle to reduce the number of broadcasts, which can reduce the channel load. A centralized routing scheme with mobility prediction is proposed,which assisted by an artificial intelligence powered software-defined network controller [11]. Similarly, Bhatia et al. [12] also combined Software Defined Networking (SDN) with machine learning algorithms, proposed a datadriven approach for implementing an artificially intelligent model for vehicular traffic behavior prediction, which has the potential to predict real-time traffic trends accurately. Due to the regular movement of buses, a new routing scheme called Busbased Routing Technique (BRT) is proposed [13], which exploits the periodic and predictable movement of buses to learn the required time for each data transmission to Road-Side-Units (RSU) through a dedicated bus-based backbone to improve the delivery ratio and reduce end-to-end delay. The development of unmanned aerial vehicles (UAVs) also provides a new solution for VANETs. Oubbati et al. [14] designed a scheme that automatically reacts at each topology variation while overcoming the present obstacles while exchanging data in ad hoc mode with UAVs, the assistance of UAVs to vehicles can improve transmission performance. With the development of 5G networks, novel four-tier architecture for urban traffic management is proposed [15]. The novel architecture shows potential for improving the efficiency of traffic management.

In this paper, we analyze the possible road traffic status and get accurate observations based on Kalman Filter, and then predict the road status based on HMM. Different routing methods are used to improve routing performance according to different road traffic conditions.

Specifically, the main contributions of the paper are as follows: 1) Kalman Filter is used to get observations, which can help to get the road status more accurately; 2) HMM-based prediction is proposed for traffic conditions on the road; 3) Choosing the appropriate routing method according to different traffic status, which can reduce the number of packets and improve the delivery rate.

The remainder of this paper is organized as follows. In Sect. 2, the network model is given. In Sect. 3, observation based on Kalman Filter are obtained. In Sect. 4, we give a prediction model based on HMM and routing method. In Sect. 5, evaluates the performance of our scheme by simulations. In Sect. 6, we conclude this paper.

2 Network Model

In this research, multi-lane unidirectional traffic flow is considered. The road between two adjacent intersection is considered a road segment, which is assumed to be much longer than the transmission range. Consider a VANET with N vehicles, denoted by a set $N : \{c_1, c_2, ..., c_N\}$, where c is used to represent the vehicle. All vehicles will move along the prescribed road and will not exceed the speed V_{max}, where V_{max} is maximum speed limited on the road. Special public buses move on fixed routes, other types of vehicles move along the roads at its own will. Each vehicle is able to acquire its own instant state on the basis of the embedded GPS. The states of vehicle c at time t constitute a five-tuple, $s_c(t) : (id, v, a, p, t)$, representing the vehicle identification, velocity (v_{xt} and v_{yt}), acceleration, position (x and y coordinates), and timestamp. The states of road r at time t constitute a six-tuple, $s_r(t) : (id, \bar{v}, \bar{a}, \sigma^2, n, t)$, representing the road identification, average velocity, average acceleration, variance, number of vehicles and timestamp. Where $\bar{v}$, $\bar{a}$ and variance respectively calculated by Eq. (1), (2) and (3):

$$\bar{v} = \frac{\sum_{i=1}^{n} v_i}{n} \tag{1}$$

$$\bar{a} = \frac{\sum_{i=1}^{n} a_i}{n} \tag{2}$$

$$\sigma^2 = \frac{\sum_{i=1}^{n} (v_i - \bar{v})^2}{n} \tag{3}$$

The basic network model is shown in Fig. 1, and divided into four road sections according to traffic intersections and signal lights. Each vehicle is equipped with On Board Unit (OBU) for wireless communications. When the distance between two vehicles is less than their transmission range, they will communicate with each other. In the case where there is an obstacle, the communication is not possible. Therefore, vehicles on different roads cannot communication with each other as shown in Fig. 1. For the entertainment application or other data sharing applications, we assume that each node always has data to send. Emergency data is also transmitted once an accident occurs. The next model process is shown in Fig. 2, and a summary of main mathematical notations is provided in Table 1.

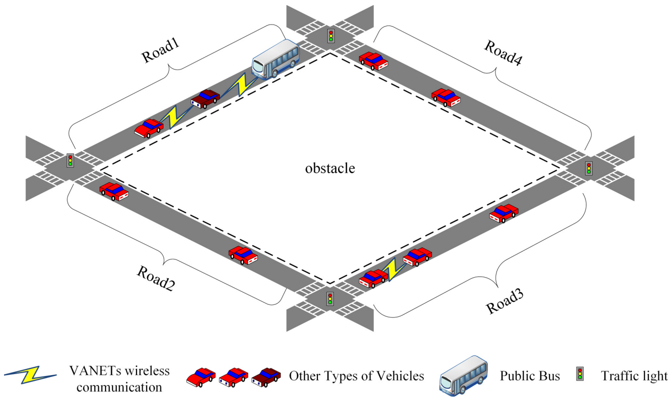

Fig. 1. Network model

Table 1. Summary of the main mathematical notations

Natation	Description
N	Road vehicle set
V_{max}	Maximum road speed limit
$\bar{v}$	Average speed of the vehicles
$\bar{a}$	Average acceleration of the vehicles
σ^2	Variance of vehicle speed
X_t	Vehicle state vector
Z_t	Measurement vector
F	State transition matrix
C	System input matrix
K_t	Optimal Kalman gain
H	Measurement matrix
π	Initial hidden state probabilities
A	Transition probabilities matrix
B	Emission probabilities matrix
O	Observation sequences

3 Observation Acquisition Based on Kalman Filter

It is necessary to correctly and promptly get the node state of VANETs for the road traffic prediction. In this section, Kalman Filter is proposed to obtain an accurate state, since the possible errors in the measured values will lead to the inaccurate prediction results.

3.1 Overview of Kalman Filter Model

Kalman Filter [16,17] is an efficient recursive filter that estimates the state of a linear dynamic system from a series of noisy measurement and can solve a set of mathematical equations for unknown state vectors in an optimal method that minimizes the estimated error covariance. Kalman Filter has two important vectors, state vector and measurement vector. We let X_t be the vehicle state vector. And the measurement vector Z_t is a measurement at time t. The Kalman Filter uses two equations: the process equation and the measurement equation. The process equation is defined as:

$$X_t = FX_{t-1} + Cu_t + \omega_t \tag{4}$$

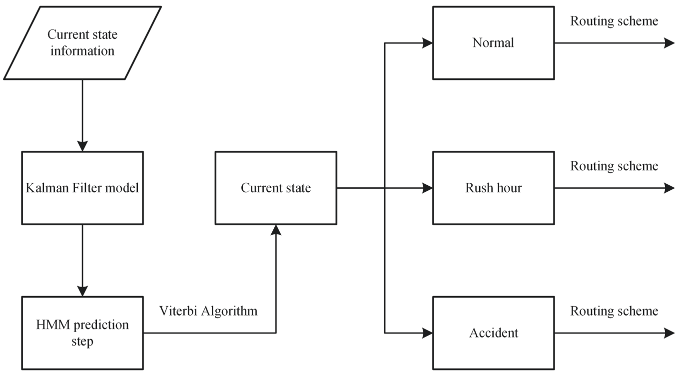

Fig. 2. Process of model

where F is a state transition matrix, C is the system input matrix and ω_t is the process noise which Gaussian distribution with zero mean and a covariance matrix Q.

The measurement equation is defined as:

$$Z_t = HX_t + \mu_t \tag{5}$$

where Z_t is the measurement vector at time t and H is the measurement matrix. μ_t is the measurement noise which is Gaussian distribution with zero mean and a covariance matrix R.

3.2 Kalman Estimation

When a node is added into the network, it will generate a state vector $SC_t = (x_t, v_{xt}, y_t, v_{yt}, a_{xt}, a_{yt})^{\mathsf{T}}$, where x_t and y_t represent the coordinates of the vehicle at time slot t, similarly, v_{xt} and v_{yt} represent the velocity of the vehicle on the x-axis and y-axis, a_{xt} and v_{yt} represent the acceleration of the vehicle on the x-axis and y-axis. According to the nodes state information on the road, the road state vector $X_t = (\bar{v}_{xt}, \bar{v}_{yt}, \bar{a}_{xt}, \bar{a}_{yt})^{\mathsf{T}}$ can be obtained. So the new speed in next step can be approximated by (6):

$$\begin{aligned} \bar{v}_{x(t+1)} &= \bar{v}_{xt} + \bar{a}_{xt}\Delta t \\ \bar{v}_{y(t+1)} &= \bar{v}_{yt} + \bar{a}_{yt}\Delta t \end{aligned} \tag{6}$$

Where acceleration is used as the system input, so we can get the 4×4 transitional matrix F and the 4×4 system input matrix C as follows in (7), (8):

$$F = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & \Delta t & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{7}$$

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

Here t is the sampling interval and corresponds to the time interval.

The Kalman Filter uses the estimation of the previous state to make a prediction of the current state according to Eq. (9):

$$\widehat{X}'_t = F\widehat{X}_{t-1} + Cu_t \tag{9}$$

where $\widehat{X}'_t$ is the predicted value based on the previous step estimated state and $\widehat{X}_{t-1}$ is the estimated state obtained in the update step.

And it uses the measured values of current state to modify the prediction value which obtained in the prediction state to obtain a new estimate value that more closely matches the real value according to Eq. (10), (11) and (12):

$$\widehat{Z}_t = Z_t - H\widehat{X}'_t \tag{10}$$

$$K_t = P'_t H^{\mathsf{T}}(HP'_t H^{\mathsf{T}} + R)^{-1} \tag{11}$$

$$\widehat{X}_t = \widehat{X}'_t + K_t\widehat{Z}_t \tag{12}$$

where P'_t is the predicted covariance matrix based on the previous step estimated covariance matrix and K_t is optimal Kalman gain. The measurement only includes $\bar{v}_x t$ and $\bar{v}_y t$, so it is also a 2×1 vector. Because the state of the road X_t is a 4×1 vector, the measurement matrix H is defined as (13):

$$H = \begin{bmatrix} 1\,0\,0\,0 \\ 0\,1\,0\,0 \end{bmatrix} \tag{13}$$

The estimation problem begins with no prior measurements. Often, the value of the first state is chosen as the first measurement value, thus $X_0' = Z_0$. After the above steps, we can get more accurate observations for the next road traffic prediction.

4 HMM-Based Road State Prediction Routing Method

Due to the increase in the number of vehicles, road conditions are becoming more and more complex and time-varying. For better V2V communication, it is necessary to analyze and predict road traffic status. In this section, we present a road state prediction based on HMM and choose the appropriate routing scheme according to different road conditions to improve routing performance.

4.1 Prediction Based on Hidden Markov Model

Hidden Markov Model is a statistical Markov model. The system is modeled as a Markov process with unobserved states. In HMM, the state is not directly visible, while the observation that depends on the state is visible. Each state has a probability distribution over the possible observation states. Therefore, the HMM can obtain the state sequence based on a series of observation sequences.

In this paper, we consider the road state to be a hidden state, and state transitions are within these hidden states. For example, a road can change from a normal non-congested state to a jamming state, or it can recover from a jamming state to a normal state. Moreover, the road traffic state cannot be directly judged from the measured date. Each road traffic state corresponds to a variety of observation states, which is also in line with the characteristics of HMM, so we use HMM to predict the road traffic state.

HMM can be defined as

$$\lambda = \{\pi, A, B\} \tag{14}$$

where π is the initial hidden traffic state probabilities. A is the transition probabilities matrix between the hidden states. And B is matrix which the probabilities of the observable states in the hidden states.

We take the speed, acceleration, the number of vehicles and the variance of the speed as the observation states (See Fig. 3). In order to easily obtain the HMM model, the road traffic state is divided into three hidden states: normal, rush hour and accident. When the road is in a normal state, we consider that the vehicle can move at a higher speed, and also consider the possibility of a slower speed due to the driver's behavior when there are fewer vehicles. When the road traffic state is at the rush hour, the number of vehicles on the road increases, which will cause road congestion with a high probability. The accident state is a traffic accident on the road. In order to simplify the model, we believe that the accident will cause partial congestion on the road and will not result in the entire road paralyzed. Therefore, the variance of the vehicle speed will be larger. So as to distinguish it from the normal state when the number of vehicles is small, the number and speed of vehicles should also be taken into consideration. The HMM is based on the historical data on the road afterward.

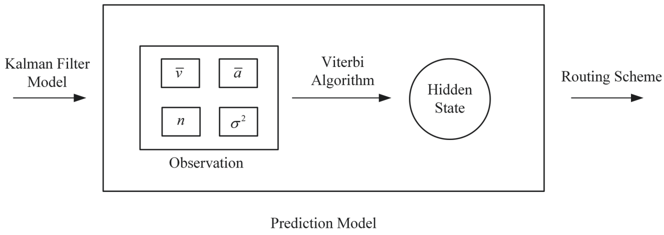

Fig. 3. Prediction based on HMM

In this paper, Viterbi Algorithm is used to accurately predict the sequence of hidden states. We know model parameters λ and observation sequences $O = (o_1, o_2, ..., o_T)$. Where T is time. First, we initialize it according to Eqs. (15), (16):

$$\delta_1(i) = \pi_i b_i(o_1) \tag{15}$$

$$\psi_1(i) = 0 \tag{16}$$

where π_i is the initial hidden state i probabilities and $b_i(o_1)$ is the probabilities of the observable state o_1 in the hidden state j in the HMM. $\delta_t(i)$ is the most likely observation sequence when the hidden state is i at time t. $\psi_t(i)$ is the most likely hidden state at time $t-1$.

Then recurse to $t = 2, 3, ..., T$:

$$\delta_t(i) = \underset{1 \leq j \leq N}{max}[\delta_{t-1}(j)a_{ji}]b_i(o_t) \tag{17}$$

$$\psi_t(i) = \underset{1 \leq j \leq N}{argmax}[\delta_{t-1}(j)a_{ji}] \tag{18}$$

where N is the number of all hidden states and a_{ji} is the transition probabilities between the hidden state i and hidden state j in the HMM.

Finally, terminating algorithm and backtracking the optimal path, $t = T-1, T-2, ..., 1$. We can get the optimal path, which is the hidden state sequence in HMM. When the model parameters and the observed state sequence are known, we can get the most likely hidden state sequence according to the Viterbi Algorithm, so that the road state observed at multiple times can be used to predict the true road state. The pseudo-code for Viterbi is given in Algorithm 1.

Algorithm 1. Viterbi Algorithm.

Input: A sequence of observations $O = o_1, o_2, ..., o_T$;
Output: The most likely hidden state sequence $I = i_1, i_2, ..., i_t$;

function VITERBI(O):I
  for each state i **do**
    $\delta_1(i) \leftarrow \pi_i b_i(o_1)$
    $\psi_1(i) = 0$
  end for
  for $t \leftarrow 2, 3, ..., T$ **do**
    for each state s_j **do**
      $\delta_t(i) = \max\limits_{1 \le j \le N} [\delta_{t-1}(j) a_{ji}] b_i(o_t)$
      $\psi_t(i) = \underset{1 \le j \le N}{argmax} [\delta_{t-1}(j) a_{ji}]$
    end for
  end for
  for $t \leftarrow T-1, T-2, ..., 1$ **do**
    $i_T = \underset{1 \le j \le N}{argmax} [\delta_T(i)]$
    $i_t = \psi_{t+1}(i_{t+1})$
  end for
return I
end function

4.2 Routing Method

If we know the hidden sequence, the appropriate routing algorithm will be chosen for different hidden states.

i) When the road is in a normal state, the vehicle is driving on the road at a high speed and the road is not congested. The target vehicle need to find other vehicles that can transmit within the communication range. If no vehicle is found within the transmission range, the vehicle will carry the information for a period of time slot s_1. During time s_1, if there is a suitable vehicle, the message will be transmitted, otherwise it will be discarded. If there is a bus in the transmission range, the data packet is sent to the bus first, because compared with other types of vehicles, the route of the bus is relatively stable, which is helpful for improving the transmission rate. As show in Fig. 4, $V1$ can communicate with $V2$. $V3$ will store the packet until it meets an appropriate vehicle or drop the packet upon reaching the maximum amount of time s_1 to hold the packet.

ii) When the road is in rush hour, there are more vehicles on the road, which will cause road congestion. Due to the excessive number of vehicles and slow speeds on the road, frequent broadcast messages will cause heavy channel load and severe packet loss. So Extended Kalman Filter (EKF) is used to predict the position of the vehicle and neighbor vehicles. KF is suitable for linear systems, while EKF can be used to solve nonlinear problems. Individual vehicle movement may be non-linear because of the complex road environment, So EKF is used to predict vehicle position. We also set a time slot s_2 and broadcast every time s_2 in order to prevent the error of EKF estimation from being amplified. As shown in Fig. 5, there are vehicles in the transmission range of $V1$. Communication is performed every time s_2 because of the large number of vehicles.

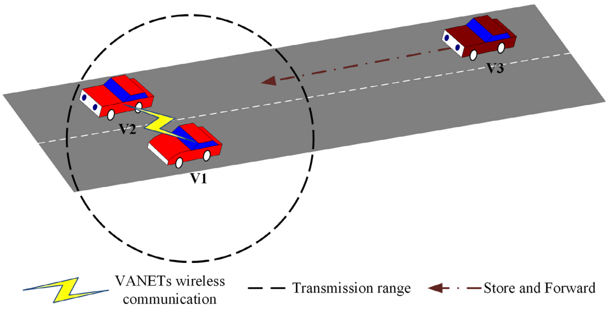

Fig. 4. Normal state

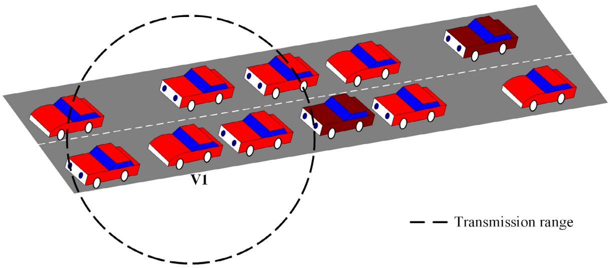

Fig. 5. Rush hour

iii) When an accident happens, it will introduce local congestion. Therefore, emergency data should be transmitted first. We will increase the priority of emergency information and extend the time to store packets in order to find a suitable next hop. As shown in Fig. 6, vehicles behind the accident site will suffer from congestion, and vehicles in other lanes will transmit emergency data first.

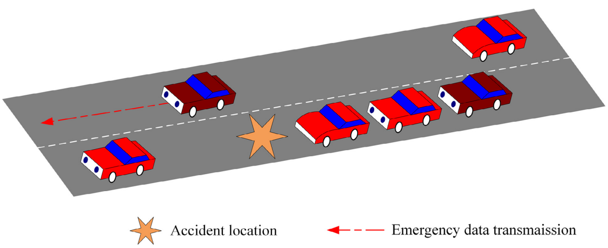

Fig. 6. Accident

Road traffic status are becoming more and more complicated due to the increase in vehicles. Encountered with different problems in different road environments, when the road is in a normal state, it is necessary to find a suitable next hop node to transmit packet. When the road is in the rush hour, there are always vehicles within the transmission range. However, due to the slow speed and the large number of vehicles, frequent broadcast messages will cause channel load and data loss. When a traffic accident occurs, emergency data should be transmitted first in order to restore traffic and reduce casualties. So we first predict the state of the road, then select the appropriate routing method to reduce the channel load and improve the packet delivery ratio. The pseudo-code for routing method selection is given in Algorithm 2.

Algorithm 2. Routing Method Selection.

```
Input: Current road traffic status I; The node set Φ;
function ROUTING METHOD(I, Φ)
    if I = NormalState then
        for each node i ∈ Φ do
            for any node j ∈ Φ || i ≠ j do
                if Distance(i, j) < transmissionrange then
                    Send Message
                else
                    Store and Forward
                end if
            end for
        end for
    else if I = RushHour then
        for each node i ∈ Φ do
            if t = s_2 then
                Broadcast message
            else
                Extended Kalman Filter
            end if
        end for
    else
        if I = Accident then
            for node i ∈ Φ || i ∉ Accident location do
                Increase the priority of emergency information
                Extend the time to store packet
            end for
        end if
    end if
end function
```

5 Simulation

In this section, some numerical results are given to show routing performance using routing scheme based on HMM prediction, which verifies the effectiveness of this method through the amount of packets and the packet delivery ratio.

5.1 Simulation Settings

We present a comparative performance study. Comparing our routing method with the hello protocol in AODV (HP-AODV) [18] and Kalman Prediction-based Neighbor Discover (KPND) [8]. The hello messaging protocol in AODV is a typical way that uses fixed time interval to broadcast. KPND uses Kalman Filter to predict the position of neighbor nodes. When the error is greater than the threshold, the neighbor table is refreshed through broadcasting. We assume that vehicles are gradually entering the road, so there are fewer vehicles on the road at the beginning of the simulation. Road traffic status will change with the increase of simulation time. When the vehicle reaches the end of the road, it randomly leaves the road or enters the next road. Public buses move on prescribed routes, and there is at most one bus on each road. All the vehicular nodes have the same transmission range. As in a typical entertainment and data sharing application of VANETs, every node always has data to transmit. All the mobile nodes have the same predefined maximum speed and the mobility generation parameters are given in Table 2. We conduct every simulation same times to achieve the average results in order to reduce the uncertainty from the random values of simulation parameters.

Table 2. Parameters for mobility generation

Parameter	Value
Simulation time (s)	200
X (m)	1000
Y (m)	1000
Max.speed (m/s)	10, 20, 30
Number of roads	4
Number of lanes	2
Max.acceleration (m/s^2)	2
Max.deceleration (m/s^2)	2
Transmission range (m)	200
Vehicle length (m)	4

5.2 Result

To measure how efficient the routing method performs, two metrics are added to analyze the routing method performance. One is the number of packets and the other is the packet delivery ratio. The results obtained by Kalman Filter are also shown. Figure 7 illustrates the error between the observed value obtained by Kalman Filter and the true value. The predicted value is calculated by the Eq. (4).

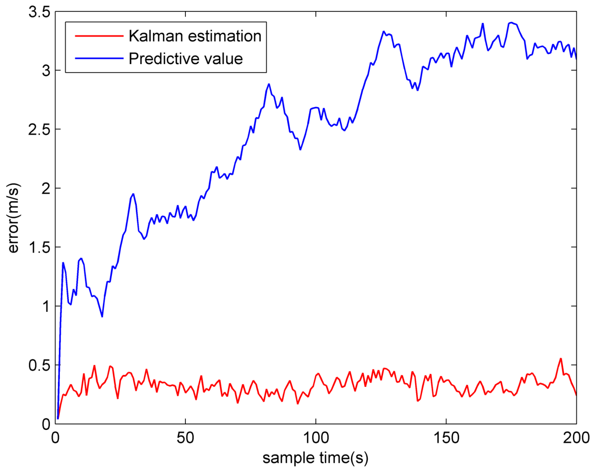

Fig. 7. Error compared to true value

We counted the total number of packets generated during the whole simulation. Figure 8 shows the number of packets generated during the simulation where the maximum speed is 30 m/s. Prediction based on HMM (PHMM) is the routing method we use. As shown in Fig. 9, the comparisons of the number of packets with different maximum speed is clearly depicted. Figure 10 shows the change in packet delivery rate over time.

5.3 Data Analysis

In Fig. 7, it can be clearly seen that the estimation based on Kalman Filter is more accurate than the predictive value. The error between the Kalman estimation and the true value is as low as 0.6 m/s, even if the increase in simulation time leads to an increase in the number of vehicles. The maximum error caused by the predictive value is 3.4 m/s, which is much larger than Kalman estimation. It is effective for obtaining accurate observation to use Kalman Filter.

At the beginning of the simulation, because there are fewer vehicles, fewer data packets are sent and the road is not congested. PHMM, AODV and KPND generate similar number of packets. When there are more vehicles, the state of

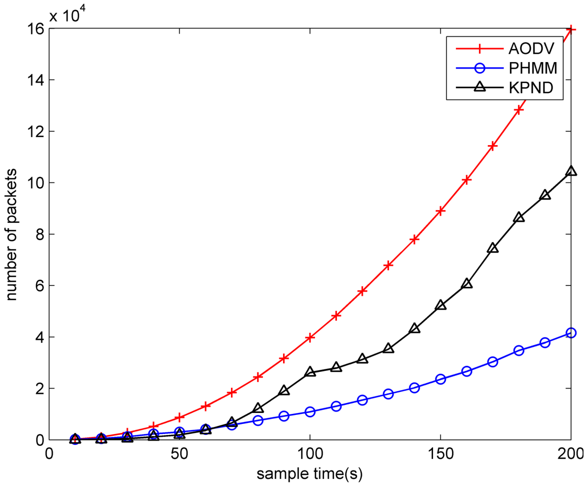

Fig. 8. Number of packets

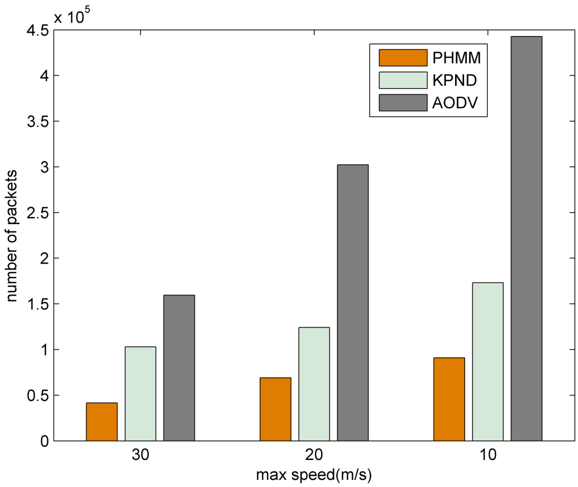

Fig. 9. The comparisons of the number of packets with different speed

the road traffic changes, and the data packets generated by PHMM are obviously less than AODV as shown in Fig. 8. As new vehicles continue entering the road, KPND needs to frequently send messages to refresh the neighbor table. So when the simulation time increases, the number of data packets sent is more than PHMM. From Fig. 9, it can be observed that PHMM can send fewer packets compared with AODV and KPND in different maximum speeds. The lower the maximum speed, the easier road becomes congested. And when the distance between vehicles become closer, it is easier to find relay nodes to transmit pack-

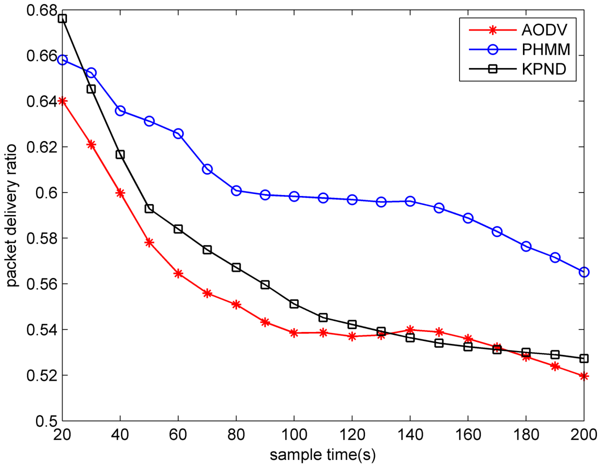

Fig. 10. Packet delivery ratio

ets, so when the maximum speed is lower, more date packets are sent. Therefore, when the maximum speed is 10 m/s, the most number of packets are sent, and when the maximum speed is 30 m/s, the least packets are sent. Among them, when the maximum speed is 20 m/s, compared with maximum speed of 30 m/s, KPND increases fewer packets, indicating that the Kalman Filter may perform well when the maximum speed is 20 m/s. As shown in Fig. 10, the value of packet delivery ratio decreased with the increase of sample time. When the number of vehicle nodes increases, the packet delivery ratio of AODV decreases faster than that of PHMM. With PHMM, we can obtain larger packet delivery ratio than using AODV. For example, under the simulation scenario of 60 sample times, the AODV results in an about 56% packet delivery ratio, but with PHMM, it yields delivery ratio of around 63%, which is 7% better than the AODV. During the whole simulation time, the packet delivery ratio of PHMM is about 5% higher than that of AODV on average. KPND shows a higher delivery ratio when there are fewer vehicles, but when there are more vehicles and the road traffic state changes, PHMM's delivery ratio is better than KPND. Because of the changing road traffic conditions, linear Kalman Filtering cannot accurately predict the position of the vehicles, and a large number of messages need to be sent to obtain the position of the neighboring vehicles. These comparisons show that PHMM is more adapted to the changing road environment.

6 Conclusion

In this paper, a routing method based on HMM is proposed to predict road status. The true state of the road is considered a hidden state in HMM. We take the speed of vehicle, acceleration, number of vehicles on the road and velocity variance as the observation states in the HMM. We can use these observation to predict whether the vehicles on the road are driving normal, congested due to rush-hours or traffic accidents. The state of road traffic is divided into three states to facilitate the establishment of HMM based on road historical data. In VANETs, to provide an accurate information transmission and a fast interaction, must find a suitable routing algorithm. But there is no single routing method which can adapt all road traffic conditions. Choosing the right routing method by predicting road conditions is a new idea. Simulation results show that compared with the AODV and KPND, our method increases the value of packet delivery ratio and decreases the number of packets in the changing road environment, and reduces the channel load.

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