

# V2X Routing in VANET based on Hidden Markov Model

Lin Yao, Jie Wang, Xin Wang, Ailun Chen, Yuqi Wang

**Abstract**—It is very hard to establish and maintain end-to-end connections in a Vehicle Ad-Hoc Network (VANET) as a result of high vehicle speed, long inter-vehicle distance and varying vehicle density. Instead, a store-and-forward strategy has been considered for vehicle communications. The success of this strategy, however, depends heavily on the cooperation among nodes. Different from exiting store-and-forward solutions, we propose a Predictive Routing based on Hidden Markov Model (PRHMM) for VANETS, which exploits the regularity of vehicle moving behaviors to increase the transmission performance. As vehicle movements often exhibit a high degree of repetition including regular visits to certain places and regular contacts during daily activities, we can predict a vehicle’s future locations based on the knowledge of past traces and hidden Markov model. Consequently, the short-term route of a vehicle and its packet delivery probability for a specific mobile destination can be predicted. Moreover, PRHMM enables seamless handoff between Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications so that the transmission performance will not be constrained by the vehicle density and moving speed. Simulation evaluation demonstrates that PRHMM performs much better in terms of delivery ratio, end-to-end delay, traffic overhead, and buffer occupancy.

**Index Terms**—Predictive Routing, VANET, HMM.

## I. INTRODUCTION

VEHICULAR Ad-hoc Network (VANET), a special type of mobile ad hoc network, is an important component of the Intelligent Transportation Systems (ITS). VANETs contain some fixed infrastructures and some vehicles, where vehicles act as mobile nodes that can carry and relay data. Each vehicle can communicate with other vehicles directly forming vehicle to vehicle communication (V2V) or communicate with a fixed road side unit (RSU), forming vehicle to infrastructure communication (V2I) [1]. V2V allows automobiles to “talk” to each other over one or multiple hops using short-range communication, but is subject to frequent communication disruption as a result of the vehicle joining or leaving from the network, different vehicle speeds or moving directions. V2I is a viable solution when V2V communications are not available, but its performance depends on specific wireless technology and communication coverage of RSUs. Due to the limitations of V2V and V2I, we consider the use of hybrid vehicular communication, named Vehicle-to-X (V2X), to enable the

seamless vehicular network connectivity in Figure 1. Two vehicles on the road can communicate either through V2V or V2I, depending on the available connections and path selection criteria.

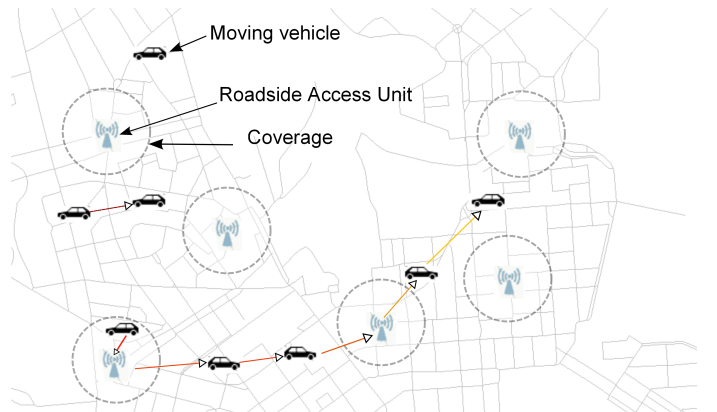


Fig. 1: Vehicular communications in ITS

The potential of hybrid communications not only helps to increase the chance of connectivity in disconnected scenarios, but also to improve the performance of message dissemination in VANETs. The performance of V2X communication, however, mainly depends on how well the messages are routed. Different from conventional networks, disconnections are the norm in VANETs. A VANET has the following salient characteristics [2]: (a) trajectory-based movements with predictable locations and time-varying topology, (b) varying number of vehicles with independent or correlated speeds, (c) frequent topology partitioning due to high mobility, and (d) reduced power consumption requirements. Consequently, conventional routing protocols based on the existence of an end-to-end connection cannot be adopted directly in this unique vehicular environment as intermediate nodes cannot always be found between a source and a destination.

VANET routing has been widely studied and investigated [3][4]. It can be classified into two types, topology-based and position-based [4]. Topology-based routing forwards packet based on the information of network links, while in geographic routing a node forwards packets based on locations of its neighbors and the destination. Without maintaining any routing table or exchanging link states within neighbors, position-based or geographic routing is considered to be more stable and suitable for VANETs. Position-based routing includes the geographic unicast and broadcast. In geographic unicast, packets are transmitted between two nodes via multiple wireless hops.

This work is supported in part by the National Natural Science Foundation of China (No.61672129) and by the Fundamental Research Funds for the Central Universities (No.DUT16QY41).

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There is a big challenge to design an efficient routing protocol to deliver a packet timely with low dropping rate in VANETs [1]. To achieve the least delay, some V2X-based geographic routing approaches are proposed in [5][6][7][8][9]. Their performance heavily depends on the vehicle density and traffic conditions. However, there is no use of prediction in these schemes. As moving paths of human often exhibit a high degree of repetition as a result of regular visits of certain places and contacts with others during daily activities, a vehicle's future locations can be predicted [10]. In [11][12][13], the possible trajectories of moving vehicles are predicted to facilitate the route finding from the source to destination. However, the routing performance of these studies is purely determined by the vehicle distribution (i.e. dense or sparse) and vehicle speeds without exploiting the fixed communication infrastructure.

In light of the problems of existing work, we propose a Predictive Routing based on Hidden Markov Model (PRHMM) to ensure more reliable and timely data transmissions in VANETs. This in turn helps improve the road safety, traffic efficiency, and remote diagnostics [14]. In the case of accident management, emergency messages may be sent to a pre-determined road rescue site upon the occurrence of an accident, such as a crash on the highway during a snow day and a car spontaneous combustion due to the stored explosives. PRHMM chooses the vehicles that have a higher probability of arriving at the rescue center as the next hops, so that rescue efforts can be organized at lower delay. PRHMM can also facilitate the transmission of real-time information from vehicles to a road traffic controller for more efficient traffic management, where the data are applied to learn the traffic flow statistics, traffic congestion conditions, and road utilization. Rather than using passive traffic detection through sensors, the real-time reports of traffic data through V2V and V2I can avoid the costs of installing and maintaining a large number of sensors [15]. Our PRHMM can also be used in the remote diagnostics, where a service station can assess the state of a vehicle without making a physical connection with the vehicle [16][17]. When a vehicle encountering the driving problem enters the area of a service garage, it can actively reply the queries from the garage. Based on the vehicle's past records (either sent by the vehicle or downloaded from Internet), the technician can diagnose the problem reported by the customer to avoid the waiting time.

Our design focuses on three challenges: i) How to effectively predict a vehicle's future locations based on its past mobility patterns; ii) How to select nodes for message relaying given the predicted movement pattern toward the destination vehicle; and iii) How to achieve automatic switch between V2V and V2I to avoid disconnections and ensure high-connectivity regardless of the scenarios and vehicle speeds in a VANET. Our scheme takes advantage of the history mobility and movement pattern to predict the future path, where the HMM model is exploited to efficiently process the time-sequence data. Our main contributions of the paper are as follows:

- (i) We propose a novel predictive routing scheme which can effectively predict a vehicle's near future path according to its past mobility trace with HMM.

- (ii) We apply a Forward-Backward Algorithm to train HM-M, which makes full use of the past mobility patterns to maximize the probability of message arriving at the destinations.
- (iii) We propose a routing decision scheme to efficiently select relay nodes for message forwarding, taking advantage of the movement pattern predicted based on the forwarding probability and delay to the destination.
- (iv) We evaluate the performance through extensive simulations. Compared with a routing protocol for intermittently connected networks (PROPHET) [18], a V2X-based approach (V2X) [6], and a cellular-based approach (GRPL) [19], our PRHMM is superior in delivery ratio, delivery latency, delivery overhead and buffer occupancy.

The remainder of this paper is organized as follows. In Section 2, we discuss related work. Section 3 describes the preliminary. In Section 4, Markov Routing Algorithm is proposed. Section 5 evaluates the performance of our scheme by simulations. Finally, we conclude the work in Section 6.

## II. RELATED WORK

Many routing protocols have been developed for VANETs, which differ in their protocols characteristics, techniques used, network structure [3]. Based on the routing information used in the packet forwarding, VANET routing protocols are classified into topology-based and position-based [3][4]. Topology-based routing schemes generally require additional node topology information during the path selection process. Geographic routing uses neighboring location information to perform the packet forwarding. Geographic routing protocols are commonly categorized into three classes [3] [4]: Delay Tolerant Network (DTN) Protocols, Non Delay Tolerant Network (Non-DTN) Protocols and hybrid.

In the DTN, communication opportunities (contacts) are intermittent. The routing challenge is to find a path that can provide the good delivery performance and low end-to-end delay in a disconnected graph where nodes may move freely. Some routing protocols choose neighbors close to the destination as next hops. The Motion Vector Algorithm (MOVE) in [20] assumes that every node has the global location information including the destination. Every node can estimate its closest distance to the destination, and determines which neighbor to forward packets to. Similar to MOVE, Scalable Knowledge based Vehicular Routing (SKVR) [21], also makes use of the destination position in the bus route to forward packets to a vehicle closer to the destination. Some approaches are based on the least delay to forward packets. In Geographical Opportunistic (GeOpps) [22], every node estimates the delay of different paths to the same destination, and selects the neighbor closer to the destination as the next hop. In the Vehicle Assisted Data Delivery (VADD) algorithm [23], every node can predict the mobility of other nodes based on the network traffic and route type, and selects a candidate node with a higher speed to achieve the least transmission delay. To achieve the least delay, some infrastructures are used to store and forward a packet when there are vehicles or other

RSUs within the communication range along the best delivery path in [5][6][7][8][9]. However, their performance is mainly determined by the vehicle density and traffic scenarios. In [11][12][13], a location-prediction-based routing algorithm is presented to discover route from the source node to the destination node. In [11], a regular flooding-based route discovery is proposed to collect the location and mobility information of nodes and store it at the destination. The destination node can predict the current location of each node using the stored information. In [12], every node will choose the encountered nodes which have the common area and the similar movement pattern with that of the destination as the best possible next-hops. In [13], variable-order Markov model is adopted to abstract vehicular mobility for an urban vehicular network environment.

Assuming there are always a number of nodes to achieve the successful communication, non-DTN protocols do not consider the disconnection issue and are only suitable for use in high density network. In the greedy approach, every node forwards its packet to the neighbor closest to the destination. But the forwarding strategy can fail if no neighbor is closer to the destination than the node itself. To solve this issue, GPSR [24] uses perimeter forwarding to decide the next hops. GPSR is a stateless protocol that the destination information in the packet header will never be updated. To address this problem, Advanced Greedy Forwarding (AGF) is proposed to incorporate the speed and direction of a node in the beacon packet and the total travel time[25]. Greedy Routing with Abstract Neighbor Table (GRANT) uses the concept of extended greedy routing to choose the next hops [26]. In the overlay routing approach, the routing protocol operates on a set of representative nodes overlaid on top of the existing network, especially in the urban environment. Nodes would forward as far as they can along roads in both greedy and perimeter mode and stop at junctions which help to decide the next hop [27]. Connectivity-Aware Routing (CAR) uses AODV-based path discovery to find routes with limited broadcast from PGB [28]. Greedy Traffic Aware Routing protocol (GyTAR) [29] tries to mimic the shortest path routing by taking into account the road connectivity based on the given number of cars. Landmark Overlays for Urban Vehicular Routing Environments (LOUVRE) [30] is a geo-proactive overlay routing where the sequence of overlaid nodes is determined. In GRLP [19], authors propose a geographic routing scheme which exploits the predictive locations of vehicles for data forwarding. Transferred messages are particularly chosen in the buffer and a cellular system is used to predict vehicle locations based on information uploaded by vehicles themselves.

Hybrid schemes are also developed because no existing routing protocol performs efficiently in all circumstances. Two or more position-based routing protocols (non-DTN and DTN schemes) are merged. Sometimes one or more topology routing protocols are merged with position-based routing in TO-GO [31] and HLAR [32].

**Summary of Related Work** In summary, though there exist many different routing approaches, most of them (including the predictive routing schemes) have their performance determined by the specific traffic scenarios and vehicle speed

in a VANET. In contrast, our work aims to design a V2X routing scheme independent of traffic conditions and vehicle speeds. Different from the works in delay-tolerant networks [19] [33] [34][35], our protocol adopts HMM to predict the future movement of a vehicle based on its past mobility traces. Different from Markov model, there is no one-to-one correspondence between the future location and the past mobility pattern in HMM. The future locations are hidden. So our model can better work in VANETs where there is no way to tell for certain which road the vehicle will be on just by checking the past mobility traces.

### III. HIDDEN MARKOV MODEL

Hidden Markov Model (HMM) is a statistical Markov model where the system is modeled as a Markov process with unobserved states. In a HMM, the state is not directly visible, but the observation that depends on the state is visible. Each state has a probability distribution over the possible observation states. Therefore, the sequence of observation states generated by a HMM gives some information about the sequence of states.

HMM can be denoted by  $\lambda = (N, M, \pi, A, B)$  or  $\lambda = (\pi, A, B)$ .

$N$  - the number of hidden states.

$M$  - the number of observable states.

$S = \{S_0, S_1, \dots, S_{N-1}\}$ , the hidden state sequence.

$O = \{O_0, O_1, \dots, O_{M-1}\}$ , the observable state sequence.

$A = \{a_{ij}\}$ , the transition probabilities between the hidden states  $S_i$  and  $S_j$ , where  $a_{ij} = P(S_j|S_i)$ .

$B = \{b_j(k)\}$ , the probabilities of the observable states  $O_k$  in the hidden state  $S_j$ , where  $b_j(k) = P(O_k|S_j)$ .

$\pi = \{\pi_i\}$ , the initial hidden state probabilities, where  $\pi_i = P(S_i)$ .

In our paper, we adopt Forward-Backward algorithm to establish an accurate Hidden Markov Model  $\lambda = (N, M, \pi, A, B)$  [36]. The correlative variables are defined as follows:

$\alpha_t(i) = P(O_1 O_2 \dots O_t, S_i | \lambda)$ , the forward variable - the probability of the cumulative observation sequence and hidden state  $S_i$  at time  $t$ , given the model  $\lambda$ .

$\beta_t(i) = P(O_{t+1} O_{t+2} \dots O_T | S_i, \lambda)$ , the backward variable - the probability of the future observation sequence until time  $T$ , given the model  $\lambda$  and the hidden state  $S_i$  at time  $t$ .

$\zeta_t(i, j) = P(S_i, S_j | O_1 O_2 \dots O_T, \lambda)$ , the probability of transitioning from the hidden state  $S_i$  at the time  $t$  to the hidden state  $S_j$  at the time  $t + 1$ , given the model  $\lambda$  and the observation sequence.

$\gamma_t(i) = P(S_i | O_1 O_2 \dots O_T, \lambda)$ , the probability of the hidden state  $S_i$  at the time  $t$ , given the model  $\lambda$  and the observation sequence.

The adjustment process of the Forward-Backward algorithm is as follows [36]:

- (i) Initialize  $\lambda = (\pi, A, B)$ .
- (ii) Compute correlation parameters  $\alpha_t(i)$ ,  $\beta_t(i)$ ,  $\zeta_t(i, j)$ , and  $\gamma_t(i)$ .
- (iii) Adjust  $\pi, A, B$  and  $\lambda$ .
- (iv) If  $P(O|\lambda)$  increases, go to (ii).

In a HMM, both transitions and observations can be used to predict the next state. The equation below is applied to predict the state distribution at time  $t + 1$  under the state distribution at time  $t$ :

$$P^{t+1}(s) \leftarrow \frac{P^t(S)P(O_{t+1}|S)}{P(O_{t+1})} \quad (1)$$

In addition,  $O_{t+1}$ , the observation at time  $t + 1$  is used to further constrain the state distribution.

$$P(O_{t+1}) = \sum_{S_i \in S} P^{t+1}(S_i)P(O_{t+1}|S_i) \quad (2)$$

#### IV. HMM-BASED ROUTING FOR VANET

In this section, we present PRHMM, a predictive routing scheme based on HMM for VANETs. PRHMM exploits vehicles to carry and forward messages. As discussed earlier, the end-to-end delivery performance will degrade significantly as a result of temporary and frequent network disconnections. The success of V2X applications relies on the network connectivity, which is possible only when there is a high vehicular density to sustain multi-hop communications or there exist fixed infrastructures such as RSUs. The aim of our work is to find some suitable relays which can forward the messages to the destination vehicle with a higher probability.

We first introduce our prediction model to predict the future movement path of a vehicle based on its past mobility traces and select a set of nodes that are more likely to reach the destination vehicle to be the relay nodes. We then define routing metrics. Finally, we will present our routing algorithm for the decision of the relay nodes to continue the packet forwarding and the corresponding routing paths.

##### A. Movement Prediction

Since the position information is available in VANETs and obviously beneficial for unicast routing, our routing scheme makes full use of the positions of the communicating nodes in determining the forwarding nodes and the transmission path. A sender can find its own position from the local GPS or other localization schemes, and obtain the position of the destination vehicle through some kind of location service [37][38]. Each vehicle can estimate its speed at a specific time based on the speed limit of the road. A vehicle broadcasts beacon messages periodically to its one-hop neighbors to announce its physical location, moving velocity and direction.

Before presenting our model for the prediction of the trip sequence, we first introduce some terminologies.

1) *Terminologies*: We have the following three terminologies:

**Link Point**: A link point represents the location and states of a vehicle, defined in terms of  $l = \{ road, speed, direction \}$ , which corresponds to a location point in Figure 2. In our digital map, road segments terminate at intersections or dead ends. Our model aims to predict the next link based on the past route of a vehicle.

**Trip Sequence**: A trip sequence is formed with a set of link points to record the moving trace of a vehicle,  $R =$

$\{l_1, l_2, \dots, l_i, \dots\}$ , where  $R$  is the collection of movement records corresponding to the observation sequence in our paper.  $l_i$  represents the  $i_{th}$  link, and the last link point represents the destination of the route. A trip sequence can be collected periodically or triggered by events. In the periodic approach, a mobile device must consider the tradeoff between achieving a higher location accuracy with more frequent recording and reducing the battery consumption with a larger recording interval. In our work, we adopt the event-triggered approach where the current location is recorded upon detecting a transition to the new road segment.

**Traversed State**: We model the sequence of traversed state  $s_i$  where  $i$  represents a discrete time variable [34]. A state  $s_i$  is represented by a pair  $\langle l_j, d_k \rangle$ , where  $l_j$  represents the  $j_{th}$  link point and  $d_k$  represents the  $k_{th}$  destination. The vehicle states are denoted as  $\dots, s_{i-2}, s_{i-1}, s_i, s_{i+1}, s_{i+2}, \dots$ , where  $s_i$  is the current state,  $\dots, s_{i-2}, s_{i-1}$  are the immediately preceding states. Based on a given set of states  $\dots, s_{i-2}, s_{i-1}, s_i$ , we will predict the future states  $s_{i+1}, s_{i+2}, \dots$ .

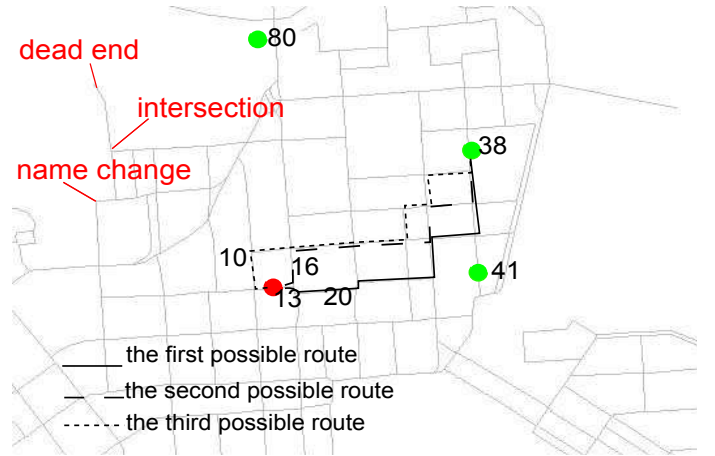


Fig. 2: Roads are represented as discrete segments. A red point represents the current location of the car, and a green point represents the possible destination of the car. 38, 41 or 80 marks a street segment.

2) *Prediction of the Trip Sequence based on HMM*: A vehicle may go to different destinations in a day such as office, home, supermarket, etc. Our model first obtains all possible destinations of a vehicle based on its historical mobility pattern and the current link information, and then predicts the trip sequence from the current location to a destination. Rather using a single location, in this work, we use the final road segment to represent a destination.

We divide the target position of a packet into two types: destination and intermediate road segment. As a vehicle is in the moving state, its final position is unknown. Thus, we consider the final vehicle position as a hidden state in a HMM, and the immediate road segments to reach by a vehicle as the observable states. The size of the transition matrix  $A$  is  $N * N$ , where  $N$  is the number of destination positions, and the size of emission matrix  $B$  is  $N * M$ , where  $M$  is the number of intermediate roads or segments.

We adopt HMM to predict the next position a vehicle will pass in the following steps. First, we find the frequently visited destination segments of a vehicle based on the visiting times recorded in the history table. Then we use these road segments as the elements of matrix  $A$ .

To form the accurate HMM, we apply the Forward-Backward Algorithm [36] to compute the four correlative variables defined in Section 3. Then, we can compute  $\overline{\pi}_i$ ,  $\overline{a}_{ij}$  and  $\overline{b}_i(k)$  based on Equation (3), (4) and (5). Finally, the accurate model  $\lambda = (\pi, A, B)$  is obtained, where  $(1, 2, \dots, t, \dots, T)$  represents the sequence of observations. At time  $t$ , the vehicle moves along a new path and updates its history table.

The expected number of times that the vehicle stays at the hidden state  $S_i$  at time  $t$  is

$$\overline{\pi}_i = \gamma_t(i) \quad (3)$$

The probability of transition from  $S_i$  to  $S_j$  is calculated as:

$$\overline{a}_{ij} = \frac{\sum_{t=1}^T \zeta_t(i, j)}{\sum_{t=1}^T \gamma_t(i)} \quad (4)$$

The probability of observing the state  $O_k$  when the hidden state is  $S_j$ .

$$\overline{b}_i(k) = \frac{\sum_{t=1, O_k}^T \gamma_t(j)}{\sum_{t=1}^T \gamma_t(j)} \quad (5)$$

In Table I,  $l_{j-1}$  is the previous road segment that the vehicle has passed by,  $l_j$  is the current road passing by, and  $d_k$  is the destination road segment.

TABLE I: The history table

$l_{j-1}$	$l_j$	$d_k$
...	...	...
7	23	13
23	27	13
27	36	13
36	13	13
13	...	...

For example, the vehicle has arrived at the road segment 13 in Figure 2. There are three possible next road segments to pass, 38, 41 and 80. Based on the transition matrix  $A$  in our HMM, the probabilities from the current segment 13 to each possible next segment are respectively  $a_{13 \rightarrow 38} = 0.3367$ ,  $a_{13 \rightarrow 41} = 0.1497$ ,  $a_{13 \rightarrow 80} = 0.2561$ . Hence, the path towards 38 is likely to be chosen as the next path. From the matrix  $B$ , we can get  $b_{13}(10) = 0.4793$ ,  $b_{13}(16) = 0.1145$ ,  $b_{13}(20) = 0.0972$ , so the probability of passing the road 10 is the largest. Consequently, the trip sequence of the vehicle can be formed.

After getting the trip sequence, every vehicle can know whether it may arrive at the destination of a packet it receives with a high probability. Then, routing metrics based on the trip sequence will be derived, which will be introduced in the next section.

### B. Routing Metrics

We define two routing metrics to evaluate a vehicle's capacity of forwarding packets, the delivery delay and the

TABLE II: Frequent notation

Notation	Description
$RSU_i$	The $i$ -th Road Side Unit
$S$	Source
$D$	Destination
$v_i$	The $i$ -th vehicle
$l_i$	The $i$ -th road
$l_c$	The current location of $v_i$
$l_d$	The destination location of $D$
$L$	The packet length
$g_v$	The transmission rate of between vehicles
$d(l_i, l_j)$	The distance between $i$ -th and $j$ -th road
$v$	The vehicle velocity

delivery probability. A neighbor can be chosen as the next hop relay only if it can balance the two metrics.

**Delivery Probability:** This is the probability of successfully delivering packets to the destination. Based on our prediction model, we can get a rough route from the current node to a destination  $D$  and estimate the delivery probability. Based on Equation (4), we can deduce the following matrix of the current node, where  $p_{i \rightarrow j}$  represents the probability from  $l_i$  to  $l_j$ ,  $n$  is the number of links from  $l_c$  to  $l_d$ .

$$P_{[n \times n]} = \begin{bmatrix} 1 & p_{1 \rightarrow 2} & \cdots & p_{1 \rightarrow n} \\ p_{2 \rightarrow 1} & 1 & \cdots & p_{2 \rightarrow n} \\ \vdots & \cdots & 1 & \vdots \\ p_{n \rightarrow 1} & p_{n \rightarrow 1} & \cdots & 1. \end{bmatrix}$$

Since there is more than one continuous path from  $l_c$  to  $l_d$ , we use  $\Gamma_j = \langle l_1, l_2, \dots, l_n \rangle$  to present the  $j$ th path, where  $l_1 = l_c$  and  $l_n = l_d$ . The probability of reaching the destination through  $\Gamma_j$  can be calculated as

$$P_i = \prod_{i, j < n} p_{i \rightarrow j}. \quad (6)$$

The probabilities for all possible paths to  $D$  will be cached and the path with the maximum probability is selected as the optimal one.

**Delivery Delay:** This is the time estimated for the current vehicle to travel from the current location to the destination location when the vehicle follows a specific path. The delivery delay over a path  $\Gamma_j$  is the total time consumed for the vehicle to reach the destination location. The delivery delay,  $d_{V2D}$ , is defined as follows:

$$d_{V2D} = \frac{L}{g_v} + \sum_{l_i \in \Gamma_j} \frac{s_{l_i}}{v}, \quad (7)$$

where  $L$  is the size of the packet, and  $g_v$  is the transmission rate of the current node.  $s_{l_i}$  is the road length of  $l_i$ , and  $\sum_{l_i \in \Gamma_j} \frac{s_{l_i}}{v}$  represents the time consumed to travel along along  $\Gamma_j$ .

### C. Routing Decision

In many cases, there are no RSUs deployed. In case that RSUs are deployed, if all vehicles resort to RSUs for communications, it would overload RSUs and lead to significant performance reduction. To ensure communications without RSUs

and reduce the burden of RSUs, packets will be preferably forwarded through V2V communications in our model. If the vehicle density is low and there exist RSUs around, V2I communications will be exploited. Finally, when neither V2V no V2I is available, packets will be carried by moving vehicles towards the destination taking advantage of their mobility. Therefore, packet routing in PRHMM follows the following basic principles:

(1) If a vehicle finds the destination within its transmission range, it will send messages to the destination directly.

(2) Else, this vehicle tries to select at most other  $N$  vehicles to route the packets based on the routing metrics.

(3) Else, if no vehicle exists in step (2), an appropriate RSU should be chosen to forward packets.

(4) Else, this vehicle stores the packet until it meets an appropriate next hop or drops the packet upon reaching the maximum amount of time to hold the packet.

In order to reliably and timely deliver a packet to its destination, it is important to find appropriate relays. The following five steps will be applied in our model for a node which holds a packet to select vehicles or RSUs as its relays to continue forwarding packets to the destination  $D$ .

In step (1),  $D$ 's information including its identifier and location  $l_d$  is broadcasted to its neighbors before sending a packet.

In step (2), each neighbor replies with the delivery delay, delivery probability and its probability of encountering an RSU.

In step (3), the node compares its own delay and delivery probability with those of neighbors. To trade off between the delivery probability and delivery delay in selecting a relay, we define a metric  $Q$

$$Q = \alpha \cdot p - (1 - \alpha) d_{v2v}, \quad (8)$$

where  $p$  represents the delivery probability to  $D$  and  $d_{v2v}$  means the delivery delay to  $D$ . The value of  $\alpha$  will be introduced in the next section. We determine if a neighbor can be a candidate relay as follows:

$$relay = \begin{cases} yes & \text{if } \frac{Q_{neighbor}}{Q_{current}} > \delta \\ no & \text{otherwise.} \end{cases}$$

If the number of neighbors that are candidate relays is more than  $N$ , we will choose the first  $N$  neighbors; Otherwise, we will choose all the appropriate neighbors.

In step (4), if  $\delta > 1$  holds, a selected relay is expected to ensure a packet to reach  $D$  with a better performance, and packets are forwarded to it.

In step (5), if  $\delta < 1$  holds, packets may be sent to an RSU. If the probability for the current node to encounter an RSU is larger than all its neighbors, it will forward packets once meeting an RSU; otherwise, packets will be sent to the neighbor whose probability of encountering an RSU is the highest. After receiving packets, an RSU will deliver packets to the destination  $D$  if it is within the transmission range; otherwise, the packets will be forwarded to its RSU neighbor which is closest to  $D$ , and the process continues. If packets reach an RSU that is closest to  $D$  but  $D$  is beyond its

TABLE III: Simulation Setup

Network area	$10 * 8km^2$
Simulation time	700k seconds
Mobility Model	WorkingDayMovement
data rate of cars and RSUs	2Mbps
transmission range	200m
packet creating time	500s-600s
packet size ranges	10B - 4KB
Number of Office	30
Number of Home	141

TABLE IV: Settings for different sets

parameter	Set1	Set2	Set3	Set4	Set5
$\alpha$	[0.1:0.9]	0.3	0.3	0.3	0.3
Vehicle No	50	[30;70]	50	50	50
RSU No	15	15	[0:40]	15	15
Speed (m/s)	2.4-13.6	2.4-13.6	2.4-13.6	[2:14]	2.4-13.6

transmission range, the RSU will send packets to a passing-by vehicle which has a higher probability of reaching  $D$ .

## V. PERFORMANCE EVALUATION

We use the Opportunistic Network Environment (ONE) simulator [39], a powerful tool developed in Java environment, to evaluate our routing protocol. The ONE simulator is designed for Delay Tolerant Networks (DTNs), and is comprised of both mobility and routing modules.

Our simulation background is the city of Helsinki in Finland. A node moves following the Working Day Movement model, which captures the regular activities of human being, including sleeping at home, working in office and visiting some places. The model follows the movement pattern of people and is verified by comparing its statistical features with the real-world traces using the metrics such as the inter-contact time, contact duration and the number of contacts per hour [10]. There are two different ways for a person to go from home to work: driving or taking the bus, with a 50% probability for each. Each person works in the office for eight hours each day. At work, the movement is limited to 10 meters. At the end of the working day, a person may go back home with 50% probability and 50% go to some other Points of Interest (POI) for shopping and other things. Each person almost follows the same track every day to the work. Buses move with the Bus Movement model, running back and forth along their routes with speeds between 7 and 10 m/s. The stopping time for buses to pick up passengers is randomly selected between 10 seconds and 30 seconds.

Table III shows the basic settings. The simulation run lasts for 700k seconds and messages are created after the first 200k seconds, with the first 200k seconds used to collect mobility traces. Each simulation is repeated 10 times with different random seeds. The transmission mode switching does not depend on the mobility or the traffic. The overall system is modeled as an alternating renewal process, where vehicular connectivity cyclically alternates among three phases, no connectivity, short-range connectivity without any RSU, long-range connectivity with a RSU. Table IV shows different settings for specific simulation sets.

We compare PRHMM with PROPHET [18], GRPL [19], and another V2X scheme [6]. PRHMM predicts a vehicle's future locations using HMM and selects the relays based on their probability of delivering packets to the destination. We choose a prediction-based scheme PROPHET [18] as a reference. In PROPHET, every node records the encounter history to form a delivery predictability vector, based on which the node can determine how likely it is able to deliver a message to the destination. Messages are only sent to the node with a higher chance of delivering the messages to the destination. PRHMM is a geographic routing scheme which exploits the history trace to predict the future location for data forwarding. Consequently, we compare PRHMM with another geographic routing scheme GRPL [19]. In GRPL, packets are forwarded to a neighbor node closest to the destination, where the neighboring vehicle locations are predicated based on their historical location and velocity data obtained from the location server. PRHMM exploits hybrid vehicular communication with automatic switching between V2V and V2I to increase the network connectivity. We thus also compare PRHMM with a V2X scheme [6]. The following metrics are used to compare these schemes:

- *Delivery ratio*: The ratio of data packets successfully delivered to destination nodes out of all the unique messages created.

- *Delivery latency*: The average delay from the time when a message is created to the time when it is successfully delivered to the destination.

- *Delivery overhead*: The average number of packets generated for each message to be sent to the destination successfully excluding the control packets.

- *Buffer occupancy*: The average amount of buffer occupied per hour per vehicle.

- *Algorithmic complexity*: To evaluate the computational speed of an algorithm, we introduce a numerical function  $T(n)$  to represent the number of times that the basic operation is repeated as a function of  $n$ .

In the remaining of this section, we provide a number of studies to evaluate the performance of our proposed scheme.

#### A. Effect of $\alpha$

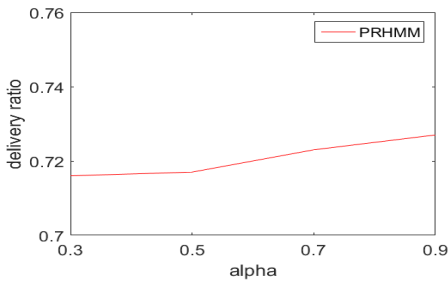


Fig. 3: effect of  $\alpha$

The parameter  $\alpha$  is used as a weight value that impacts the delivery probability and the delivery delay when making the routing decision. In this set of simulations,  $\alpha$  changes from 0.1 to 0.9. Figure 3 shows the change trend between the delivery

latency and  $\alpha$ . Obviously, the delivery ratio increases as  $\alpha$  becomes larger. When  $\alpha = 0.9$ , the delivery ratio reaches the maximum.

#### B. Effect of vehicle density

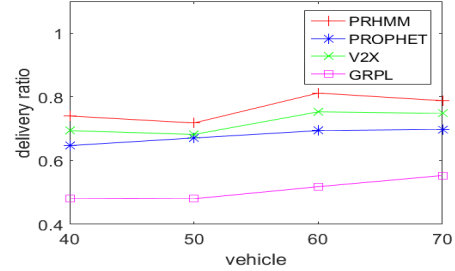


Fig. 4: Delivery ratio with different vehicle numbers

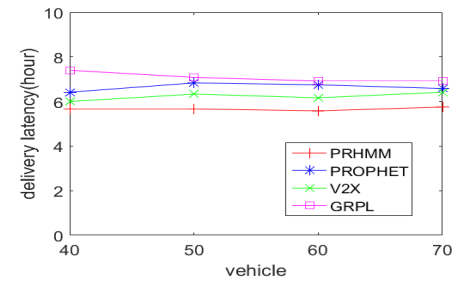


Fig. 5: Delivery latency with different vehicle numbers

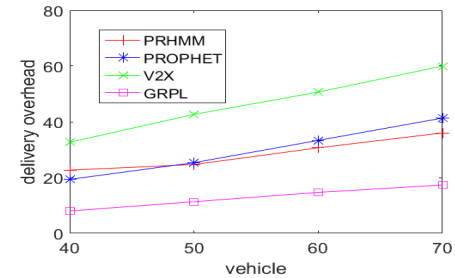


Fig. 6: Overhead with different vehicle numbers

We vary the number of vehicles from 40 to 70. In Figures 4 and 5, our PRHMM is seen to possess the highest delivery ratio and the lowest latency regardless of the vehicle density. Because vehicles can resort to RSUs to forward packets in PRHMM and V2X, they can have higher delivery ratio and lower latency than PROPHET and GRPL. V2X heavily rely on RSUs for forwarding with a lower chance of using vehicles. PRHMM takes advantage of the vehicles to avoid overloading RSUs to reach the destination thus having a lower latency. Purely relying on V2V, it is hard for vehicles in PROPHET or GRPL to find a relay to forward packets. In GRPL, the future location of a relay is predicted based on its location at a previous time instant thus the location is time-lagged. It is well known that in geographic routing, the destination location is crucial for making the forwarding decisions. If the location

information is time-lagged and deviates from the real one, a relay node selected may not be able to forward packets to the destination. In addition, it may be hard to find a relay that has a lower geographic distance to the destination in many cases. Therefore, PRHMM can achieve higher delivery ratio and lower latency than V2X, PROPHET and GRPL. From Figure 5, we can see the delivery latency keeps stable for all four schemes. PRHMM can reduce the latency 11.2% compared to V2X, 15.5% compared to PROPHET and 20% compared to GRPL.

In Figure 6, the overhead of PRHMM is seen to be smaller than V2X and PROPHET. In PROPHET, packets are forwarded to nodes which are predicted to have a higher chance of encountering the destination. In PRHMM, packets are forwarded to nodes which have a higher probability of arriving at the destination. In V2X, vehicles only forward packets to the nearest neighbors.

When with 70 vehicles, PRHMM's overhead is 41.97% and 15.6% less than those of V2X and PROPHET, respectively. Figure 6 shows that GRPL possesses the smallest overhead. In GRPL, every vehicle should upload its states (location, velocity, etc) to central server periodically, however, this overhead is not taken into account.

### C. Effect of RSU number

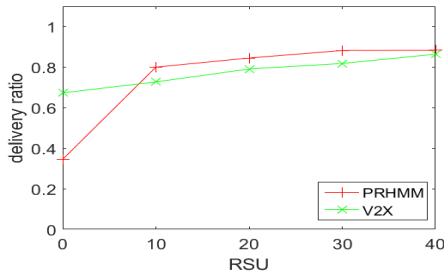


Fig. 7: Delivery ratio with different number of RSUs

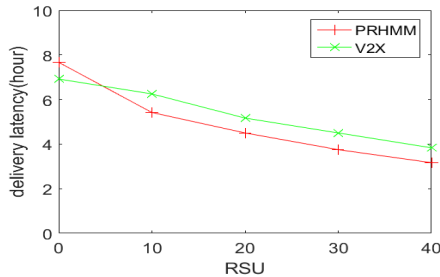


Fig. 8: Delivery latency with different number of RSUs

We only compare PRHMM and V2X as they exploit use of RSUs. In PRHMM, packets are preferably forwarded through V2V communications. If the vehicle density is low and there exist RSUs around, V2I communications will be exploited.

Figures 7 and 8 show our PRHMM in most cases performs better than V2X both in terms of the delivery ratio and latency when there exist RSUs. When there are fewer RSUs, packets

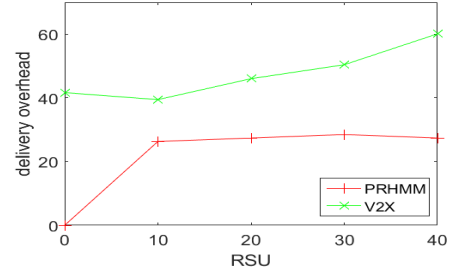


Fig. 9: Delivery overhead with different RSU

in V2X are spread between vehicles within a cluster. While in PRHMM, only the vehicles with better performance metrics are selected as relays. With fewer candidate relays to choose from, RSU has a higher chance of being resorted to. Due to the competition in accessing the limited number of RSUs, PRHMM has a lower delivery ratio and a higher delivery latency than V2X. With the increase of RSUs, PRHMM performs better than V2X, because PRHMM has more strict rule to choose the next hops and only appropriate relays (including RSUs and vehicles) are selected.

In Figure 9, the overhead of PRHMM is seen to be lower than that of V2X. As only the neighbors with better forwarding metrics can be candidate relays, fewer relays are chosen in PRHMM, which leads to fewer packets in the network. With more RSUs, additional RSUs may be also selected to forward packets, causing the overhead to increase in both V2X and PRHMM. The overhead of PRHMM is 50% less than that in V2X because only appropriate relays are chosen in PRHMM. After the number of RSUs is more than 10, the delivery overhead is stable in PRHMM, as packets will be preferably forwarded through V2V communications thus the delivery has less dependence on the number of RSUs.

### D. Effect of vehicle speed

In this set of simulation, Figure 10 and Figure 11 show that the delivery ratio decreases and delivery latency increases. As a vehicle moves faster, it is more difficult to find appropriate neighbors to forward packets and vehicles have less time interval to forward messages.

For example, a neighbor may move away while the packets are on its way to the neighbor, which causes a lower delivery ratio and higher delivery latency. However, the delivery ratio of PRHMM is 16.05% higher than that of V2X and 66.44% higher than that of GRPL. The delivery latency of PRHMM is 12.1% lower than that of V2X, 7% lower than that of PROPHET, and 18.26% lower than that of GRPL. GRPL is a geometric routing protocol, where a node makes a forwarding decision based on the destination location retrieved from the location server. As the node locations are updated to the server periodically, the accuracy will reduce when nodes move faster, which compromises the delivery ratio and delay of GPRL. With the support of RSUs, the performance of PRHMM is less impacted.



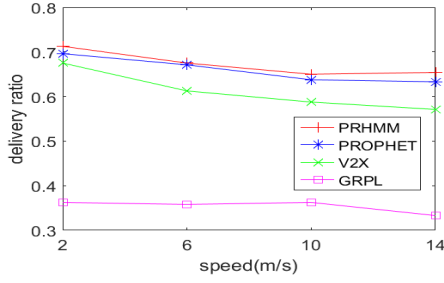


Fig. 10: Delivery ratio with different vehicle speed

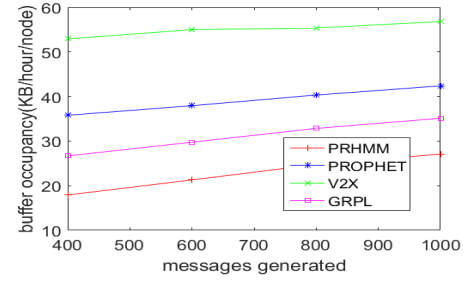


Fig. 12: Buffer occupancy

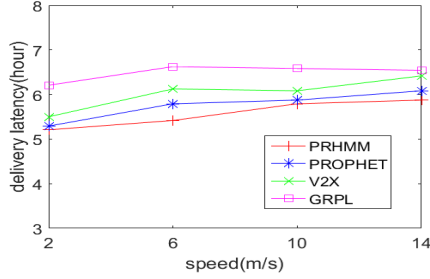


Fig. 11: Delivery latency with different vehicle speed

### E. Buffer occupancy

In Figure 12, we compare the buffer occupancy with the buffer size set to 60K. When the number of messages sent is 400, compared to V2X, PROPHET and GRPL, the buffer occupancy of PRHMM is 68.03%, 52.72% and 34.92% lower respectively. PRHMM chooses a limited number of relays as next hops based on the metric built using HMM. In PROPHET, messages are only sent to the node with a higher chance of delivering them to the destination, and this node may be even farther away from the destination. In GRPL, messages are only sent to a neighbor which is closest to the destination. The future location of a neighbor is predicted based on its history location and velocity obtained at a previous time instant from the location server. Because the location information is time-lagged and deviates from the real one, a selected relay may not be appropriate to forward packets to the destination, which causes more copies to be transferred. In the V2X algorithm, the node simply forwards each packet to the nearest neighbor, which may not have a higher chance of encountering the destination, or not have the closer distance to the destination. With inefficient packet forwarding, this algorithm has the highest buffer occupancy. In the worst case with 1000 messages sent, the buffer occupancy of PRHMM is 52.32%, 26.10% and 22.87% lower than that of V2X, PROPHET and GRPL respectively. The results demonstrate the effectiveness of our proposed algorithm in tracking the delivery states of vehicles and guiding the routing.

### F. Algorithmic complexity

We compare the algorithm complexity of all routing algorithms and summarize the results in Table V.

PROPHET predicts the delivery probability based on the historical encounter information between nodes, and applies

this predicted value as the routing metric. Two encounters exchange the summary vectors, each containing the delivery predictability of its sender to other nodes in the network. As each of the two encounters needs to update its delivery predictability to all other nodes in the network, this process incurs a complexity of  $O(n)$ . A node will simply forward its packets to the encountered node which has a higher delivery predictability. Consequently, the overall complexity of PROPHET is  $O(n)$ .

GRPL is a geographic information-based routing scheme. Before sending a new packet, the source node queries the location server for the current location of the destination and appends it to the packet header. It uses a greedy forwarding algorithm for the choice of relay nodes and the neighbor closest to the destination is selected as the next hop. It includes a location prediction, where a node predicts the future location of each neighbor based on its history location and velocity. For a network of  $n$  nodes, the prediction complexity is  $O(n)$ . During the packet forwarding, the node chooses the neighbor closest to the destination as the next hop. The forwarding complexity is  $O(n)$ . Consequently, the algorithm complexity of GRPL is  $O(n)$ .

The V2X algorithm aims to achieve the seamless connectivity by switching between V2I and V2V. The propagation delay between two vehicles is used as the routing metric. There are 3 phases in the V2X algorithm. In the no-connection phase, no V2V or V2I is available so the packet must be carried by the node itself. The time complexity is  $O(1)$ . In the short-range connection phase, V2V is available and the messages are forwarded to the closest neighbor, with the assumption that this takes the smallest propagation time to forward the packet. For a network of  $n$  nodes, the complexity is  $O(n)$ . In the long-range connection phase, V2I is available. As the next hop is an RSU, the complexity is in a constant  $O(1)$  time. Therefore, the final complexity of V2X reaches  $O(n)$ .

The core of our PRHMM algorithm is to establish a hidden Markov model, using the forward-backward algorithm to model the position information and observation state. As defined before,  $N$  is the number of hidden states which is the number of road segments a vehicle may reach, and  $M$  is the number of observable states corresponding to the number of road segments the vehicle has passed. PRHMM is composed of movement prediction and routing decision. During the predictive process, the forward (or backward) variable for a certain time depends on the  $N$  states of the previous time

(or the next time), and it requires  $N$  cycles to compute the correlation parameters  $\alpha_t(i)$ ,  $\beta_t(i)$ ,  $\zeta_t(i, j)$  and  $\gamma_t(i)$ . Therefore, the time complexity of building the prediction model is  $O(N^2)$ . In addition, as we use the observable state sequence  $O = \{O_0, O_1, \dots, O_{M-1}\}$  to establish the prediction model, the complexity of the sequence of observations is proportional to  $M$ . Consequently, the complexity of building HMM is  $O(M * N^2)$  time. Because each observation state corresponds to a hidden state,  $N$  is equivalent to  $M$ , so the complexity of building HMM is  $O(M^3)$ . During the routing decision, if no predicted vehicle exists, the packet is sent to the nearby RSU in a constant time  $O(1)$ ; otherwise, as PRHMM can select multiple relays, the node sorts the neighbors in the descending order of  $Q$  in Equation (8). The complexity is  $O(n \lg n)$  with  $n$  representing the number of vehicles. Accordingly, the overall complexity of PRHMM is  $O(M^3 + n \lg n)$ . The number of road segments  $M$  is generally much smaller than the total number of vehicles in the network  $n$ .

From the above discussion, we can get Table V. The complexity estimation is very conservative. In reality, these operations are related to relay selection and performed with only neighboring nodes, whose number is much smaller than  $n$ . The current processors can easily handle the computations of all these algorithms. It is important that PRHMM can achieve much more reliable and faster message distributions.

TABLE V: Complexity of the routing algorithm

Algorithm	Complexity
PROPHET	$O(n)$
GRPL	$O(n)$
V2X	$O(n)$
PRHMM	$O(n \lg n + M^3)$

## VI. CONCLUSION AND FUTURE WORK

In this paper, we propose a hybrid vehicular routing scheme which exploits both V2V and V2I to improve the transmission performance in VANET. We adopt HMM to predict the vehicle's future path based on the historical mobility pattern. Based on the transition matrix of HMM, we derive the probabilities for a vehicle to move from its current segment to each possible next segment. We select the forwarding relay by trading off between the delay and probability for neighboring vehicles to forward packets to the destination. The transmission will be switched from V2V to V2I if no immediate relay can be found but there exists an RSU within the communication range, and to opportunistic routing otherwise.

We have performed extensive simulations to compare PRHMM with several other state-of-the-art schemes in delivery ratio, delivery latency, delivery overhead, and buffer occupancy. We have also analyzed the algorithmic complexity to evaluate the computational speed of each algorithm.

In our future work, we plan to have a real-world implementation to further verify the performance.

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