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Intermittent Geocast Routing in Urban Vehicular Delay Tolerant Networks

Zhiyuan Li* and Panpan Wu

Abstract: Nowadays, both vehicular active safety service and user infotainment service have become two core applications for urban Vehicular Delay Tolerant Networks (uVDTNs). Both core applications require a high data transmission capacity over uVDTNs. In addition, the connection between any two vehicles in uVDTNs is intermittent and opportunistic. Intermittent data dissemination over uVDTNs is a stringent and challenging issue. In this paper, we propose Intermittent Geocast Routing (IGR). For the first step, IGR has to estimate the active connection time interval via the moving directions and velocities between any two vehicles. Second, the throughput function for uVDTNs is fitted by building a wavelet neural network traffic model. Third, the throughput function within the effective connection time interval is integrated to obtain the forwarding capability estimation of the node. Fourth, a high-efficiency geocast routing algorithm using the node forwarding capability for uVDTNs is designed. Finally, IGR is simulated on the opportunistic Network Environment simulator. Experimental results show that IGR can greatly improve the packet delivery ratio, transmission delay, delay jitter, and packet loss rate compared with the state of the art.

Key words: urban vehicular delay tolerant networks; geocast routing; node forwarding capability; connection time

1 Introduction

Vehicular networks are increasingly attracting the attention of academia and the industry nowadays. A vehicle equipped with wireless communication adaptors is regarded as a node in Vehicular Ad hoc NETworks (VANETs)[1]. Such vehicles can share their messages via wireless peer-to-peer communications, which provide considerable safety and comfortable services[2]. The Vehicle-to-Vehicle (V2V) communication mode has become increasingly important because of its outstanding potential to address safety and congestion challenges at a lower operational cost[3]. Various data dissemination applications in vehicular networks need more stringent delay requirements. Hence, V2V routing protocols have become increasingly important under vehicular network environments[4, 5].

This study focuses on efficient data dissemination of VANETs and Vehicle Delay Tolerant Networks (VDTNs). Data dissemination for VDTNs is more stringent and challenging than that for VANETs because of the intermittent and opportunistic connection between any two nodes. Also, VDTNs are an innovative solution that exploits only opportunistic connectivity among vehicles moving in surrounding areas to achieve greedy data forwarding[6]. Routing algorithms for vehicular networks can be divided into two categories: connection-aware routing[7–11] and geographic information routing[12–18]. The advantages of connection-aware routing are a higher success rate of data dissemination and lower data retransmission

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times; the disadvantage is that it cannot guarantee the quality of multi-service disseminations. The increasing number of GPS-equipped vehicles makes geographic information routing a more efficient data dissemination strategy for vehicular networks than connection-aware approaches. However, geocast routing protocols are unsuitable for sparse physical environments; an urban network is better suited. Notably, in an urban network, intersections pose a unique challenge to routing protocols. Geographic routing is essentially used to transfer packets between any two intersections on the selected path. However, most geographic routing protocols in vehicular networks do not take the connectivity time and the forwarding capability of vehicles into consideration. Hence, the performances of routing protocols need to be optimized further to improve the quality of various time-sensitive vehicular applications.

To overcome the aforementioned problems, we propose an Intermittent Geocast Routing (IGR) with storage-carry-forward mode in urban VDTNs (uVDTNs). IGR works in two modes, namely, intersection mode and road segment mode. In the intersection mode, the characteristic of network connectivity is analyzed to obtain the connectivity probability of any road segment. The maximum connective road segment is selected as the next hop. Then, in the chosen road segment, the vehicular nodes first estimate the effective connection time interval by the actual road and vehicle conditions. Next, we can fit the throughput function of a vehicle via the historical and predictive network traffic of a node, and the throughput function within an effective connection time interval is integrated to obtain the node forwarding capability estimation. Lastly, we designed an efficient IGR algorithm by integrating the road segment mode into the intersection mode for uVDTNs.

The remainder of this paper is structured as follows: Section 2 introduces network models and assumptions. Section 3 elaborates the system model of IGR for uVDTNs. Experimental simulations and their analyses are described in Section 4. Section 5 introduces the related works. Section 6 concludes this paper.

2 Network Models and Assumptions

As shown in Fig. 1, vehicular nodes transmit the bundle to the relay node after meeting the relay node. Then, the relay node deals with the bundle and transmits it to the subsequent requesting vehicles. The bundle includes the position coordinates, the direction, and the speed of the vehicles.

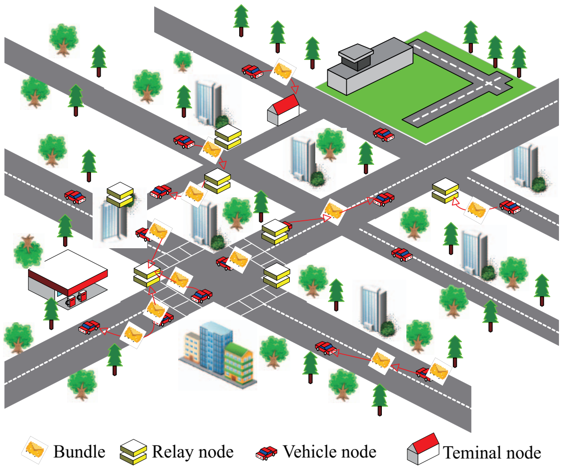


Fig. 1 uVDTNs network model.

The following are two regular assumptions of data dissemination for VDTNs[19–22]:

(1) Data dissemination of vehicle nodes uses "storage-carry-forwards" mode and multi-hop forwarding;

(2) Vehicle nodes are selfless and trusted.

The abovementioned two assumptions can be understood to indicate that when a vehicle node encounters another vehicle node on the road, they can exchange bundles with each other. Geocasting is built on top of traditional local broadcast and routing protocols to enable a vehicle to spread a bundle message to a particular spatial neighborhood. Thus, long trips might be facilitated by using multi-hop matches in which the data message changes vehicles to reach its final destination, as shown in Fig. 2.

3 System Model

3.1 Overview: IGR scheme

According to the vehicle's different positions in a city network, IGR works in two modes: the intersection

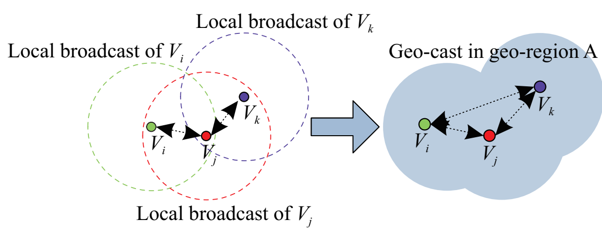


Fig. 2 Multi-hop forwarding in geocasting.

mode and the road segment mode. Figure 3 illustrates our model.

Intersection mode. In this mode, the coordinator (supported by the intersection infrastructure I, shown in Fig. 3) calculates the network connectivity of all the adjacent intersections, and the maximum connective road segment is selected as the next transmission path. When a source vehicle enters a road segment, it first sends a request to coordinator I for the road segment situations. Then, the coordinator replies with the connective quality information of road segments. The vehicle node at the intersection forwards data packets to its neighboring vehicle on the selected road segment with maximum forwarding capability.

Road segment mode. When a packet travels on a road segment, the segment mode is enabled. In this mode, (1) the effective connection time interval is estimated between any two vehicles. Adaptive threshold, Thres, is set by taking the average effective connection time of all its neighbor nodes. Relay candidate node is selected if its effective connection time exceeds the threshold value Thres. (2) According to the characteristics of historical traffic of vehicular networks, source nodes construct the predicted traffic model of the wavelet neural network to fit the throughput function of vehicle nodes. (3) The throughput function within an effective connection time interval is integrated to obtain the estimated value of the node forwarding capability. (4) The next-hop relay forwarding node is the one with the maximum average forward capability.

3.2 Analysis of the connectivity probability based on vehicular communication

Network connectivity has become the main

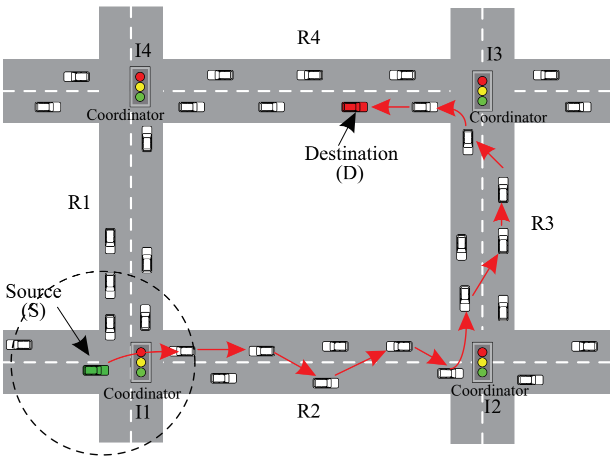


Fig. 3 Illustration of our model.

performance metric for inter-vehicle communications because a vehicle may have difficulties delivering messages to other vehicles at heavy loads. In this paper, the connective characteristics of VANETs are studied in the free-flow state. The road is divided into $n \times n$ lanes. L and W are labeled as the length and the width, respectively, for each lane. R and X represent a communication range and the spacing between two consecutive vehicles, respectively. The two assumptions are described below.

(1) M discrete levels of constant speed v_i ($i = 1, \ldots, M$) exist on the lane, where the speed v_i is independent identically distributed and independent of the inter-arrival time. The random variable v_i obeys the normal distribution[23, 24].

(2) The stochastic process of a vehicle driving into the lane in the free flow state follows the Poisson distribution with the parameter of λ_i ($i = 1, \ldots, M$). And the sum of λ_i ($i = 1, \ldots, M$) equals the parameter $\lambda(\sum_{i=1}^{M} \lambda_i = \lambda)$, where λ is the average number of vehicles driving into the lane per unit time interval. Assume that the vehicles driving into the lane are independent of each other. Thus, the occurrence probability of every speed level is $p_i = \lambda_i / \lambda$.

3.2.1 Network connectivity modeling

The inter arrival time obeys Erlang distribution. Thus, the cumulant distribution function of the vehicle spacing X_i is shown in Formula (1).

$$P\left(X_i < x\right) = P\left(v_i \Delta T_i < x\right) =$$
$$P\left(\Delta T_i < \frac{x}{v_i}\right) = \frac{(k\lambda)^k}{(k-1)!} \int_0^{\frac{x}{v_i}} \mathrm{e}^{-k\lambda t} \cdot t^{k-1} \mathrm{d}t \tag{1}$$

where ΔT_i represents the inter-arrival time of the vehicle with the speed v_i.

When $k = 1$, Formula (1) can be simplified as Formula (2), namely, the first-order Erlang distribution.

$$P\left(X_i < x\right) = P\left(\Delta T_i < \frac{x}{v_i}\right) = 1 - \mathrm{e}^{-\lambda_i \cdot \frac{x}{v_i}} = 1 - \mathrm{e}^{-\frac{\lambda_i}{v_i} \cdot x} \tag{2}$$

Assume $X = \min(X_1, X_2, \ldots, X_M)$, we can get Formula (3).

$$P\left(X < x\right) = 1 - P\left(X \geqslant x\right) =$$
$$1 - P\left(X_1 \geqslant x, X_2 \geqslant x, \cdots, X_M \geqslant x\right) =$$
$$1 - \mathrm{e}^{-\sum_{i=1}^{M} \frac{\lambda_i}{v_i} \cdot x} \tag{3}$$

Hence, the vehicle spacing X between any two vehicles obeys an exponential distribution with the parameter of $\sum_{i=1}^{M}\frac{\lambda_i}{v_i}=\lambda\sum_{i=1}^{M}\frac{p_i}{v_i}$. Then, we can obtain the average vehicle density ρ_{avg} shown in Formula (4).

$$\rho_{\text{avg}}=\frac{1}{E\left(X\right)}=\lambda\sum_{i=1}^{M}\frac{p_i}{v_i}=\lambda E\left(1/v\right) \tag{4}$$

The speed variable v obeys the normal distribution, and its probability distribution function is shown in Formula (5).

$$f\left(v\right)=\frac{1}{\sigma\sqrt{2\pi}}\mathrm{e}^{-\frac{(v-\mu)^2}{2\sigma^2}},\quad v_{\min}<v<v_{\max} \tag{5}$$

where $v_{\min}$ and $v_{\max}$ represent the minimum and the maximum speeds, respectively.

Then, we can obtain the Gaussian probability density function of $f(v)$, which is shown in Formula (6).

$$\hat{f}(v)=\frac{f(v)}{\int_{v_{\min}}^{v_{\max}}f(v)\mathrm{d}v}=\frac{2/\sigma\sqrt{2\pi}}{\mathrm{erf}\left(\frac{v_{\max}-\mu}{\sqrt{2}\sigma}\right)-\mathrm{erf}\left(\frac{v_{\min}-\mu}{\sqrt{2}\sigma}\right)}\mathrm{e}^{-\frac{(v-\mu)^2}{2\sigma^2}},\quad v_{\min}<v<v_{\max} \tag{6}$$

Next, Formula (7) is derived from Formulas (4)–(6).

$$\rho_{\text{avg}}=\int_{v_{\min}}^{v_{\max}}\frac{\hat{f}(v)}{v}\mathrm{d}v=\frac{2\lambda/(\sqrt{2\pi}\sigma)}{\mathrm{erf}\left(\frac{v_{\max}-\mu}{\sqrt{2}\sigma}\right)-\mathrm{erf}\left(\frac{v_{\min}-\mu}{\sqrt{2}\sigma}\right)}\int_{v_{\min}}^{v_{\max}}\frac{1}{v}\mathrm{e}^{-\frac{(v-\mu)^2}{2\sigma^2}}\mathrm{d}v \tag{7}$$

Hence, we can obtain the average number of vehicles N_{avg}, which is shown in Formula (8).

$$N_{\text{avg}}=L\rho_{\text{avg}} \tag{8}$$

According to Formula (3), we can obtain the cumulative distribution function of the vehicle spacing $F(X_i)=1-\mathrm{e}^{-\rho_{\text{avg}}\cdot X_i}$. Then, we can acquire the connectivity probability of N_{avg} vehicles on the road segment, which is shown in Formula (9).

$$P_{N_{\text{avg}}}=P\{X_1<R,X_2<R,\cdots,X_{N_{\text{avg}}-1}<R\}=\sum_{j=1}^{N_{\text{avg}}-1}P\{X_j<R\}=(1-\mathrm{e}^{-\rho_{\text{avg}}\cdot R})^{L\cdot\rho_{\text{avg}}-1} \tag{9}$$

3.2.2 Connectivity simulation and analysis

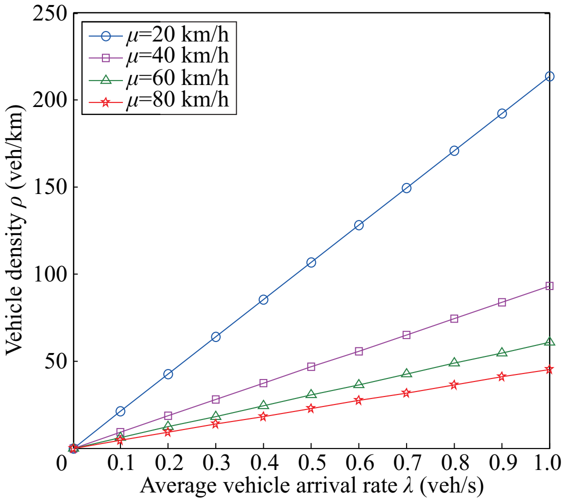
In this section, the uVANETs connectivity is simulated and analyzed. The simulation parameters are described in Table 1. The vehicle speed and the free traffic flow on roads are independent, and the lane length L is 10 km. The vehicle arrival rate obeys the Poisson distribution with the parameter X ranging from 0.5 veh/s to 0.8 veh/s. The vehicle speed obeys the normal distribution. The average vehicle speed u (km/h) and its standard deviation σ (km/h) is shown in Table 1.

Table 1 The vehicle speed and its standard deviation.

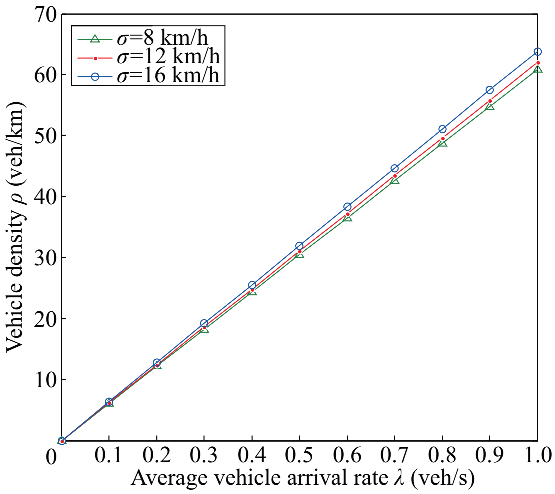
Average speed μ (km/h)	Standard deviation σ (km/h)
20	4
40	8
60	12
80	16

Figure 4 shows that the relationship between the vehicle arrival rate and the density of the vehicle flow. Figure 4a is the relationship of the vehicle arrival rate and the density of the vehicle flow when the standard deviation σ is constant and the mean speed μ changes, and Fig. 4b is the relationship of the vehicle arrival rate and the density of the vehicle flow when the standard deviation σ changes and the mean speed μ is constant. As shown in Fig. 4a, the variable ρ increases linearly with the increase of the variable λ, and the ρ value decreases with the increase of the μ value. From Fig. 4a, we can conclude that with the increase of the λ value, the distance between any two vehicles on a lane shortens significantly; hence, the connectivity between any two vehicles is more reliable and stable. Furthermore, as shown in Fig. 4b, the variable ρ also linearly increases with the increase of the variable λ, and the variable ρ is directly proportional to the variable σ. From Fig. 4b, we can conclude that with the increase of the σ value, the average vehicle density ρ for VANETs becomes much greater. Hence, the variable ρ and the variable σ are a positive correlation.

As shown in Fig. 5, the connectivity probabilities of uVANETs for the various scenarios exponentially increase with the increase of the communication radius R. Moreover, the connectivity probabilities of vehicular networks for the various scenarios are greater than 90 percent when the communication radius R is at least as great as 350 m. From the simulation results, we can conclude that with the increase of the density of the vehicle flow and the communication radius of vehicles, the connectivity probability between any two vehicles for vehicular networks tends to be stable when the communication radius R is at least as great as 350 m. The higher connectivity strategy is a key basis of route choice for further research on routing over urban vehicular networks.



(a) $\mu \in \{20, 40, 60, 80\}$ km/h, σ=8 km/h



(b) μ=60 km/h, $\sigma \in \{8, 12, 16\}$ km/h

Fig. 4 Vehicle arrival rate versus the vehicle density.

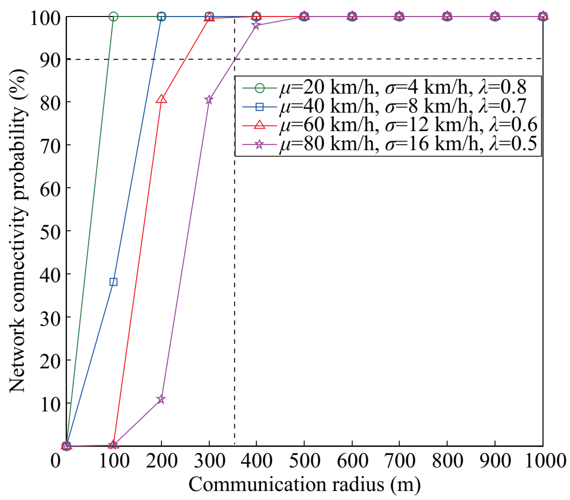


Fig. 5 Network connectivity probability with various conditions.

3.3 Average forwarding capability estimation

3.3.1 Effective connection time estimation among nodes

Effective connection time estimation among nodes is the key point to guarantee normal communications between two vehicle nodes. As shown in Fig. 6, we estimate the effective connection time between vehicle nodes i and j. The position coordinates (x_i, y_i) and (x_j, y_j), the speeds v_i and v_j, and the directions θ_i and θ_j of vehicle nodes i and j can be obtained via the GPS system. In this case, the communication distance between the vehicle nodes i and j is defined as r. Hence, the effective connection time estimation between any two nodes is described in Fig. 6 below.

The speed and distance of vehicle nodes in horizontal and vertical directions are given by Formula (10).

$$\alpha = v_i \cos\theta_i - v_j \cos\theta_j, \quad \beta = v_i \sin\theta_i - v_j \sin\theta_j,$$
$$\mu = x_i - x_j, \quad \delta = y_i - y_j \tag{10}$$

where α and β are the component differences of speed of vehicles i and j in the horizontal and vertical directions, respectively. μ and δ are the component differences of location of the two vehicles in the horizontal and vertical directions, respectively.

After the time Δt, the linear distance between the two vehicles is r and Formula (11) can be obtained according to the Euclidean distance. The maximum communication distance r between any two vehicles is less than or equal to 300 m.

$$(\mu + \alpha \cdot \Delta t)^2 + (\delta + \beta \cdot \Delta t)^2 = r^2, \quad r \leqslant 300\,\text{m} \tag{11}$$

We can get parameter Δt, which is the estimated value of effective connection time T, according to the discriminant of a quadratic equation in one unknown.

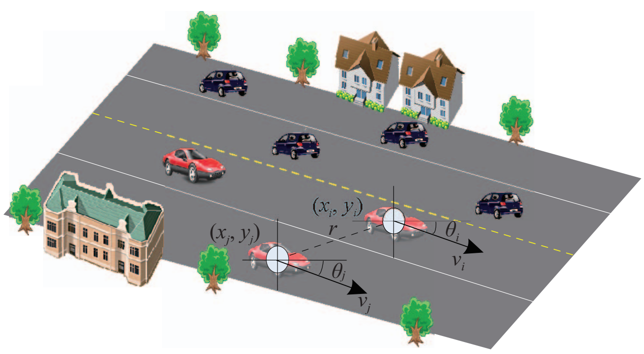


Fig. 6 Effective connection time estimation between vehicle nodes i and j.

$$T=\frac{\sqrt{(\alpha^2+\beta^2)r^2-(\alpha\delta-\beta\mu)^2}-(\alpha\mu+\beta\delta)}{\alpha^2+\beta^2},$$
$$r\leqslant 300\,\mathrm{m} \tag{12}$$

Vehicle nodes in uVDTNs exchange real-time location information, including location coordinates, moving speed, and direction angle of nodes, to neighbor nodes periodically, thereby allowing vehicle nodes to obtain information about the surrounding vehicles. The effective connection time can be estimated with Formula (12) between surrounding nodes.

3.3.2 Average forwarding capability calculation

In this paper, we use WiBro network multimedia datasets from Seoul, Korea[25]. The WiBro network is selected because it has many similarities with the vehicular network based on IEEE 802.11p. For example, both networks are wireless broadband networks, they belong to mobile applications, and they have downloading and uploading bandwidths of up to 6 and 1 Mbps, respectively, at the speed of 60–100 km/h. Reference [25] collects data from cars and trains at a high speed, and their multimedia data types include CBR and VOIP data, which are also similar to our application scenarios. Thus, we believe that WiBro can simulate real vehicular network traffic.

(1) Wavelet neural network based on network traffic prediction

The wavelet neural network structure is shown in Fig. 7. In the figure, the input layer inputs p time series values and the hidden layer contains n neurons, while the output layer has only one neuron and the output is the prediction value of the number $k+l$ time series.

In addition, w_{ij}^m represents the weight value from the neuron i in the layer $m-1$ to the neuron j in the layer m, a_{jk}^m represents the first k times input of the neuron j in layer m, ψ_m represents the transfer function of the layer m, and b_{jk}^m represents the corresponding output of the layer m. a_{jk}^m and b_{jk}^m are as shown in Formulas (13) and (14).

$$a_{jk}^m=\sum_i w_{ij}^m b_{ik}^{m-1} \tag{13}$$

$$b_{jk}^m=\psi_m(a_{jk}^m) \tag{14}$$

For the three-tier network architecture, $b_{jk}^1=X_{k-j+1}b_{jk}^3=\hat{X}_{k+l}$ and the transfer function of hidden layer uses Morlet wavelets, as shown in Formula (15).

$$\psi(t)=\cos(1.75t)\mathrm{e}^{-t^2/2} \tag{15}$$

We can obtain a_{jk}^2, b_{jk}^2, and $\hat{X}_{k+l}$, as shown in Formulas (16)–(18).

$$a_{jk}^2=\sum_{i=1}^{p} w_{ij}^2 x_{k-j+1} \tag{16}$$

$$b_{jk}^2=\psi\left(\frac{a_{jk}^2-b_j}{a_j}\right) \tag{17}$$

$$\hat{X}_{k+l}=\sum_{j=1}^{n} b_{jk}^2 w_j^3=\sum_{j=1}^{n}\psi\left(\frac{a_{jk}^2-b_j}{a_j}\right)w_j^3 \tag{18}$$

All the parameters in the above formula can be represented by θ, the network input is a time sequence of p elements, which can be expressed as $[X_k, X_{k-1}, \ldots, X_{k-p+1}]$ and the output is the predicted value $\hat{X}_{k+l}$ at the moment of $k+l$.

We can use the mean square error function of the predictive value as the objective function $C(\theta)$.

$$C(\theta)=\frac{1}{2}(\hat{X}_{k+l}-X_{k+l})^2 \tag{19}$$

To minimize the error and obtain the optimal network model parameters, conjugate gradient descent method is used to calculate the minimum of the error function, as shown in Formulas (20)–(23).

$$h(a_i)=\frac{\partial C}{\partial a_i}=-\sum_{k=1}^{N} e_k w_i \xi_i a_i^{-1}\{1.75\sin(1.75\xi_i)+$$

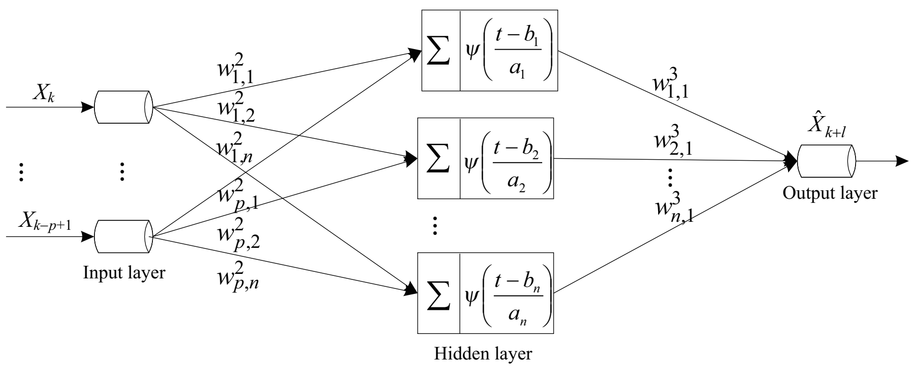


Fig. 7 Wavelet neural network structure.

$$\xi_i\cos(1.75\xi_i)\}\mathrm{e}^{-\xi_i^2/2} \quad (20)$$

$$h(b_i)=\frac{\partial C}{\partial b_i}=-\sum_{k=1}^{N}e_k w_i \xi_i a_i^{-1}\{1.75\sin(1.75\xi_i)+$$

$$\xi_i\cos(1.75\xi_i)\}\mathrm{e}^{-\xi_i^2/2} \quad (21)$$

$$h(w_i)=\frac{\partial C}{\partial w_i}=-\sum_{k=1}^{N}e_k\cos(1.75\xi_i)\mathrm{e}^{-\xi_i^2/2} \quad (22)$$

$$\begin{aligned} w_i(m+1)&=w_i(m)-\alpha h(w_i),\\ a_i(m+1)&=a_i(m)-\alpha h(a_i),\\ b_i(m+1)&=b_i(m)-\alpha h(b_i)\end{aligned} \quad (23)$$

If the absolute value of the error function is less than a predetermined threshold value, then the network learning will be stopped. Otherwise the above steps will be repeated.

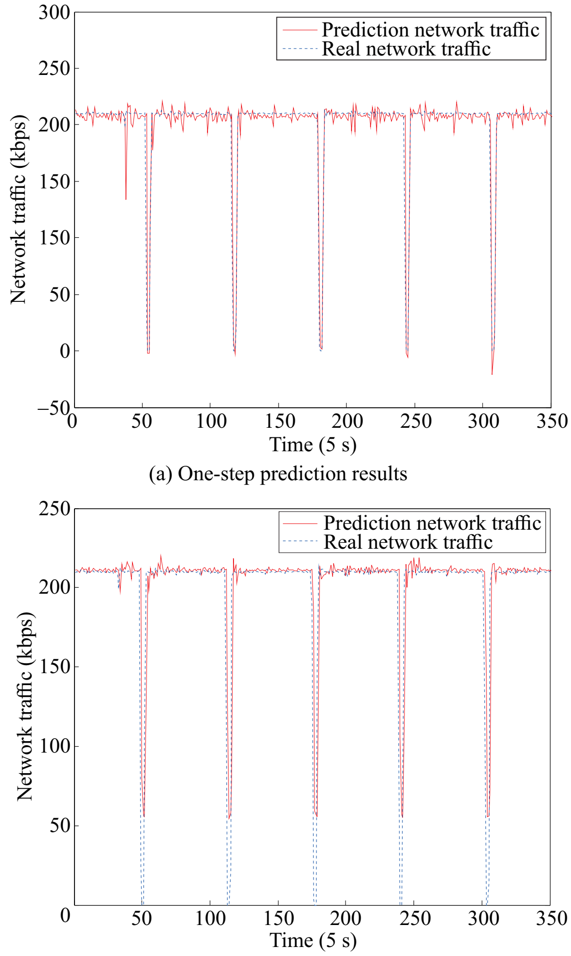
(2) Network traffic prediction verifications

The original WiBro network traffic in the data sets[25] is recorded in the check-in way, which means a new record would emerge any time network traffic is produced. Hence, the time interval between any two adjacent records is not constant, which does not satisfy the precondition of time series analysis. We set 5 s as a time unit in our experiment. After the time unit is set, the records in the datasets are divided into many continuous blocks in chronological order, and the time interval of any two adjacent blocks is identical. The blocks are sequentially numbered $1, 2, \ldots, n$. The network traffic at time span t is the time sequence between zero and the time t. Then, the wavelet neural network is simulated on Matlab R2012a. We adopt 8-15-1 network architecture in the experiment. The initialization parameters are set; for instance, the maximum training step equals 1000 epochs, the training function is the wavelet function, and the training goal equals 0.01.

Figures 8a and 8b show the one-step ahead and five-step ahead traffic prediction results, respectively. The two figures indicate that the traffic prediction curve coincides with the real network traffic curve. Hence, we can obtain the vehicular networks traffic data set $[\hat{X}_{k+l}, \ldots, \hat{X}_{k+2}, \hat{X}_{k+1}, X_k, X_{k-1}, \ldots, X_{k-p+1}]$, which consists of the historical, present, and future traffic, and then obtain the throughput function $F(x)$ via fitting the time sequence.

(3) Average forwarding capability calculation

Given the highly dynamic network environment, the connectivity and bandwidth between nodes are



(a) One-step prediction results

(b) Five-step prediction results

Fig. 8 Performance evaluation of our model.

unstable. The traffic prediction model is only an estimation value of the future time and cannot accurately describe the forwarding capability of the vehicle nodes. We fully consider the available bandwidth of a vehicle in the past, present, and future, and use the numerical integration to obtain a metric of node forwarding capability. This metric can more accurately reflect the forwarding ability of nodes and support the effectiveness and stability of vehicular networking routes.

The node forwarding capability estimation E_{NFC} is actually to calculate the trapezoid area with curved edge of throughput function $F(x)$. The throughput function within an effective connection time interval is integrated to obtain the estimated value of the node forwarding capability E_{NFC}, which can intuitively reflect the throughput of the candidate forwarding nodes in future connection periods and support the design of uVDTN data dissemination. Provided that the effective connection time interval between vehicle nodes is $[0, T]$, we can obtain the average forwarding capability of nodes by integrating the throughput forwarding function $F(x)$ in the effective connection time, as shown in Formula (24).

$$E_{\mathrm{NFC}} = \int_0^T F(x)\mathrm{d}t \tag{24}$$

3.4 IGR algorithm design

The IGR algorithm is described as Algorithm 1.

In the data transmission process, the vehicle node dynamically selects a relay node with suboptimal forwarding capability computed by Formula (24) to provide a forwarding service when more than one vehicle send data to the same optimal relay node simultaneously. At the same time, the relay node cannot provide forwarding services for one or more nodes because of its limited forwarding capability. In addition, the priority for packets is set, and higher priority packets are forwarded preferentially. When data packets have the same priority, IGR forwards the smaller packets preferentially. This strategy makes data distribution services for numerous vehicles effective and avoids some interruptions of data forwarding tasks while multiple vehicle nodes send data to the same optimal node simultaneously.

4 Simulation and Performance Analysis

4.1 Simulation and parameter settings

We use Opportunistic Network Environment (ONE)[26] as the simulation platform for IGR performance evaluation. As shown in Fig. 9, 125 moving vehicles exist in Helsinki. The wavelet neural network structure is 8-15-1, that is, it consists of eight input layer neurons, 15 hidden neurons, and one output neuron. Other relevant experimental parameters are shown in Table 2.

The proposed IGR algorithm is compared with the classical intersection-based Connectivity Aware Routing (iCAR)[8] in terms of four aspects, namely, packet delivery rate, average transmission delay, delay jitter, and packet loss rate, which are defined as follows.

Definition 1 Packet delivery rate is the ratio of the number of successfully delivered packets to the total number of delivered packets.

Algorithm 1: IGR pseudocode description.

```
If the source node S is at an intersection then
    go into intersection mode
    calculate connectivity of all the adjacent intersections
    selecte the road segment with the highest connectivity
    go into the road segment mode
else go into the road segment mode
        set U ← ∅
        for each node N_nb within the communication radius r
                of S do
            calculate T between S and N_nb
            if T_α is greater than the adaptive threshold, Thres, then
                U ← U ∪ {N_nb}
            end if
        end for
        for each node N_cd ∈ U do
            construct traffic prediction model
            estimate the forwarding capability of N_cd
        end for
        in set U, select the node N_best with the maximum
                forwarding capability
        let N_best be the next-hop
end if
```

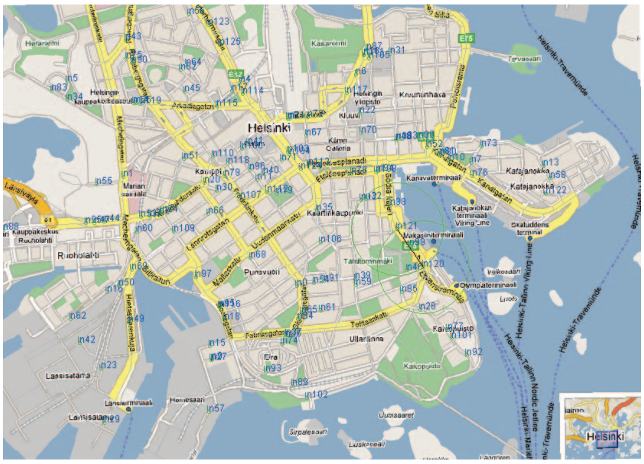


Fig. 9 Simulation experimental senario.

Table 2 Simulation experimental parameters.

Parameter	Description	Defaults
MovementModel.worldSize (m^2)	Simulation scene area	4500×3400
Scenario.endTime (h)	Simulation time	12
Scenario.nrofHosts	Total number of vehicles	125
BtInterface.type	Communication interface type	SimpleBroadcast
BtInterface.transmitSpeed (Mbps)	Transmission bandwidth	6
BtInterface.transmitRange (m)	Transmission distance	350
Mobility speed (km/h)	Moving speed of nodes	20–40
Packet.Size (10^6)	Packet size	0.5–1
Packet.Interval (s)	Interval generated by data packet	5
Packet.TTL (min)	Packet lifetime	300

Definition 2 Average transmission delay is the average value of time to send all successfully delivered packets.

Definition 3 Delay jitter reflects the change degree and stability of the delay. It is especially important for multimedia services.

Definition 4 Packet loss rate indicates the ratio of transmitted packets to the lost number of packets.

4.2 Performance analysis

4.2.1 Packet delivery ratio

Figure 10 shows a comparison of the packet delivery ratio of different numbers of packets. The successful packet delivery ratio of IGR is nearly stable at 80%, whereas that of *i*CAR is nearly 60% and decreased significantly along with an increase in the number of packets. Both algorithms belong to the connection-aware routing with both road segment selection and next-hop selection mechanism. However, *i*CAR selects the road segment only according to the number of vehicles, history transmission delay, and a distance apart from the destination node. Then, *i*CAR employs a greedy-based next-hop selection to choose the next forwarder for a packet being transmitted, which does not take into account the road communication probability and node forwarding capabilities. IGR studies the road connectivity with the time interval obeying the Erlang distribution to select better road connectivity for data forwarding. In the next-hop selection mechanism, IGR is based on node forwarding capability, and the throughput function within an effective connection time interval is integrated to obtain the estimated value of the node forwarding capability. IGR is always able to maintain a high packet delivery ratio with the increase of network load because it always actively chooses the node with the maximum node forwarding capacity as the next hop to forward data.

4.2.2 Average transmission delay

A comparison of the average transmission delay of the IGR and *i*CAR with different numbers of sending packets is shown in Fig. 11. The increasing number of packets would inevitably lead to inter-vehicle path changes and network congestion, thereby causing delay and increasing node moving velocity and network load. Simulation results show that the average transmission delay of both algorithms increases with the increase of network load, whereas the transmission delay of the proposed IGR is always lower than that of the *i*CAR. This result is obtained because although the transmission delay depends on the bandwidth between nodes for both IGR and *i*CAR, the *i*CAR only selects the node with the greedy algorithm to forward data without taking the inter-node transmission network bandwidth into account, thereby increasing transmission delay and transmission interruption times. In IGR, the network traffic predictive model using the wavelet neural network is designed to obtain the throughput function of the vehicle node; this throughput function is regarded a metric to select the next hop and thus solve the problem efficiently. Hence, the average transmission delay of IGR is lower than that of *i*CAR.

4.2.3 Delay jitter

Figure 12 shows a comparison of the delay jitter of IGR and *i*CAR. Generally speaking, the fast movement of nodes and the increase of network load inevitably

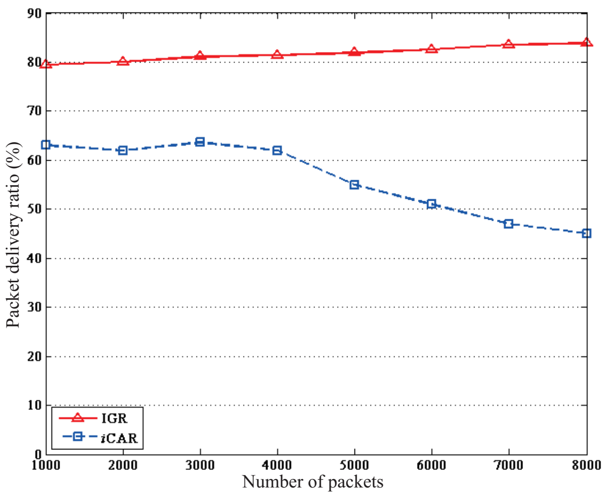


Fig. 10 Packet delivery ratio comparision.

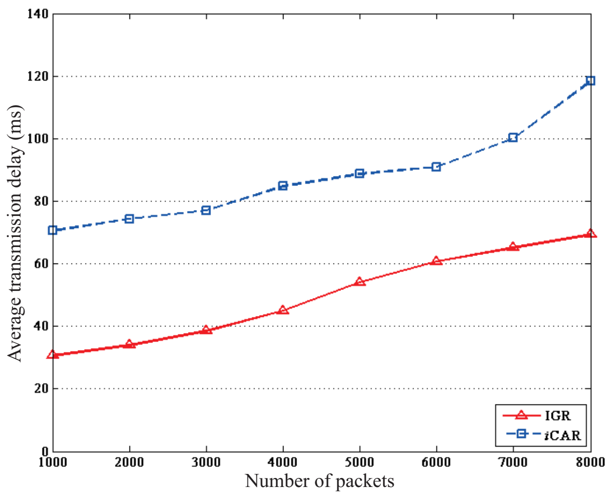


Fig. 11 Average transmission delay comparision.

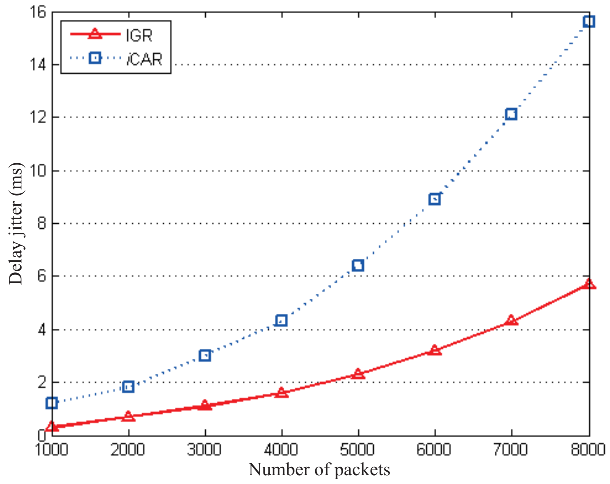


Fig. 12 Delay jitter comparision.

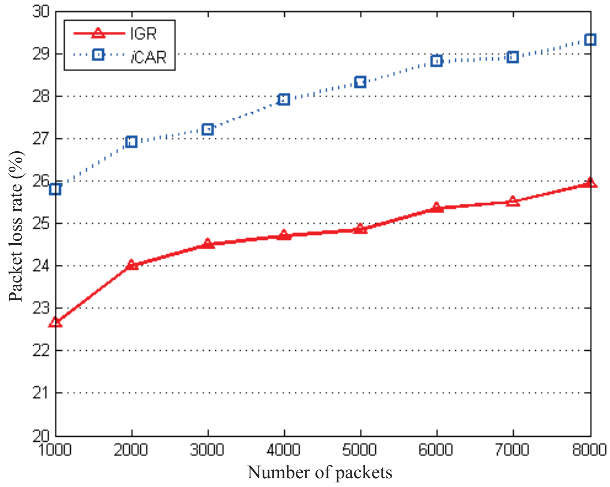


Fig. 13 Packet loss rate comparision.

lead to changes in inter-vehicle route, as well as to network congestion and delay jitter of packet transmission. The objective is to control the delay jitter within a reasonable limit to guarantee the quality of service under VDTNs multimedia service environment. Evidently, the delay jitters of IGR and *i*CAR are positively correlated with the number of packets from the simulation results, that is, delay jitter increases with the increase of the number of sent packets. However, the delay jitter of IGR remains far below that of *i*CAR because IGR can accommodate more data with a greater throughput window by selecting the next node with the maximum throughput value. Hence, the delay jitter of IGR will be smaller with the increase of the number of sent packets across the network. As for *i*CAR, data retransmission will occur when the packet throughput is larger than the capacity of the data transmission throughput window, thereby increasing delay jitter as a result of the small throughput window of *i*CAR.

4.2.4 Packet loss rate

A comparison of the packet loss rate of the two routing methods is shown in Fig. 13. Packet loss rate is closely related to network bandwidth, buffer size, and connection time between nodes, which affects the packet loss rate and the key performance indicators of the algorithm from different aspects. Thus, separately considering one factor while ignoring the other factors will increase the packet loss rate and seriously affect the network service quality and the user experience. The experimental results shown in Fig. 13 indicate that the packet loss rate of IGR is significantly lower than that of *i*CAR; thus, IGR achieves more obvious advantages with the increase of network load. The buffer size settings of IGR and *i*CAR are the same with the experiment parameters that were set. Thus, the packet loss rate index is correlated only with the network bandwidth and the connection time between nodes. The *i*CAR algorithm takes only road traffic information into account and does not further estimate these two indicators, thereby increasing the packet loss rate. IGR has better data forwarding capacity and congestion avoidance capability because it organically combines the network bandwidth with the effective connection time in the calculation process of node forwarding capacity estimation based on vehicle traffic information and historical vehicle network traffic. Thus, the performance indicator of packet loss rate is improved significantly.

5 Related Work

An increasing number of routing protocols for VANETs have been proposed recently, and these protocols can be classified into two categories: connection-aware routing and geographic routing.

5.1 Connection-aware based routing

Connection-aware based routing algorithms aim to improve the routing performances over the vehicular networks by enabling selecting roads with guaranteed connectivity and reduced delivery delay. Adaptive Connectivity-Aware Routing (ACAR)[7] is a typical connection-aware based routing protocol, which adaptively selects an optimal route with the best network transmission quality based on statistical and real-time density data that are gathered through an on-the-fly density collection process. ACAR consists of two parts. The first part is the selection of an optimal route that consists of road segments with the best estimated transmission quality. The second part is the design of an efficient multi-hop routing algorithm in each road segment. Both *i*CAR and *i*CARII[8, 9] are classical routing protocols that take the real-time vehicular traffic information and the experienced packet delivery delay per road into consideration to improve the routing performance. Both protocols use the greedy forwarding strategy to forward packets and can dynamically select road segments with guaranteed connectivity and reduced delivery delay by proactively estimating the connectivity of road segments and the minimum forwarding lifetime per road segment. CSR in Ref. [10] utilizes vehicle distribution information collected by intersection infrastructure to help vehicles select a road segment that not only ensures progress to their destination but also has better network connectivity. Reference [11] presents an anchor-based connectivity-aware routing protocol, which is a hybrid routing protocol that uses both greedy forwarding and the store-carry-forward approach to minimize the packet drop rate. The advantage of the routing protocol is that it selects an optimal route to ensure connectivity of routes with more successfully delivered packets. However, connection aware based routing cannot guarantee the quality of service of active safety and infotainment data dissemination.

5.2 Geographic information based routing

Road perception based geographical routing[12] is a representative geographic information based routing protocol. It incorporates relative distance, moving direction, and intermediate forwarders with traffic density to forward data to the destination. Hashem et al.[13] introduced the ant colony system into a data dissemination protocol and proposed the SAMQ protocol. The SAMQ protocol can compute an efficient route with multiple QoS constraints. To mitigate the risks inherited from selecting the best computed route that may fail at any moment, SAMQ utilizes situational awareness levels and ant colony system mechanisms to prepare certain countermeasures with the aim of ensuring reliable data transmission. SCRP[14] is a distributed routing protocol that computes end-to-end delay for the entire routing path before sending data messages by building stable backbones on road segments and connecting them at intersections via bridge nodes. These nodes assign weights to road segments on the basis of collected information about delay and connectivity. Routes with the lowest aggregated weights are selected to forward data packets. References [15, 16] take the number of packet copies into consideration in routing and use geographical location data to improve the data delivery probability and resource utilization rate. IBFP[17] sets Virtual Ports (VPs) at each intersection, which is served by a stopped vehicle that is waiting for the traffic light in front of the intersection. A VP gathers all the packets that need to be forwarded from all passing vehicles and transmits all the copies of the packets to the next VP when it leaves this intersection. The epidemic process exists among VPs only, thereby creating packets to be transmitted to every intersection in a short period of time with the movement of VPs. Reference [18] proposed a greedy routing scheme that created a routing path with the minimum number of intermediate intersection nodes while taking connectivity into consideration. The scheme introduces backbone nodes that provide connectivity status around an intersection, thereby enabling a packet to be forwarded in the changed direction by tracking the movement of the source as well as the destination. However, most geographic information based routing protocols in vehicular networks do not take the connectivity among vehicles and rerouting strategy into consideration. For example, in sparse vehicular networks, the relay vehicle cannot easily discover the next hop along the road to continue forwarding the packet, thereby resulting in a long transmission and wait delay. Hence, the main challenge for geographic information based routing is the optimization of data transmission capability during the effective connectivity time.

6 Conclusion

In this paper, we propose IGR for uVDTNs. IGR works in two modes: the intersection mode and the road segment mode. In the intersection mode, the network connectivity of the road segment is modeled by the time interval between any two vehicles following the Erlang distribution. The transmitted message is forwarded to the road segment with a higher connectivity probability. Then, the road segment mode is enabled. In this mode, the effective connection time interval is first estimated according to actual road conditions, vehicle nodes' direction of movements, and velocity. Then, the network traffic predictive model using the wavelet neural network is designed. Afterwards, the throughput function within an effective connection time interval is integrated to obtain the estimated value of the node forwarding capability. Next, the IGR algorithm using greedy forwarding is designed. In the algorithm, the vehicular node with the maximum forwarding capability is selected as the next hop until the message is transmitted to the destination. Simulation results show that the overall performances of our scheme are better than those of the classical vehicular routing *i*CAR model in urban traffic environments.

Acknowledgment

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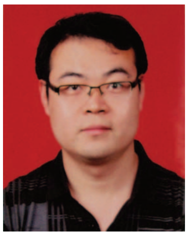

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