

LER-GR: Location Error Resilient Geographical Routing for Vehicular Ad-hoc Networks

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Abstract: The efficiency and scalability of geographical routing depend on the accuracy of location information of vehicles. Each vehicle determines its location using Global Positioning System (GPS) or other positioning systems. Related literature in geographical routing implicitly assumes accurate location information. However, this assumption is unrealistic considering the accuracy limitation of GPS and obstruction of signals by road side environments. The inaccurate location information results in performance degradation of geographical routing protocols in vehicular environments. In this context, this paper proposes a location error resilient geographical routing (LER-GR) protocol. Rayleigh distribution based error calculation technique is utilized for assessing error in the location of neighbouring vehicles. Kalman filter based location prediction and correction technique is developed to predict the location of the neighbouring vehicles. The next forwarding vehicle (NFV) is selected based on the least error in location information. Simulations are carried out to evaluate the performance of LER-GR in realistic environments, considering junction-based as well as real map-based road networks. The comparative performance evaluation attests the location error resilient capability of LER-GR in a vehicular environment.

1. Introduction

The recent advances in the area of computing, automaton, sensing, communication and networking technologies for vehicles are shifting the focus from traditional vehicular ad-hoc networks (VANETs) to an emerging field called “Internet of vehicles” (IoV) [1], [2]. These advancements give rise to a wide range of value added services for users which includes infotainment, traffic management, vehicle safety, and location-based services. All these applications require efficient routing protocols for information dissemination. A geographic routing protocol uses location information of vehicles to transmit information. The efficiency and scalability of a geographic routing protocol depend on the accuracy and the availability of the location information of vehicles [3], [4].

The related literature assumes accurate location information from GPS receivers in geographic routing protocols [5]–[11]. Nevertheless, the assumption is unrealistic, particularly in vehicular environments. In many situations, the GPS receivers calculate wrong positions of the vehicles due to the loss of satellite signals resulting from signal reflections, blocking, and interference [12], [13]. A GPS receiver might also lose satellite signals on roads near multi-floor bridges, tunnels and flyovers [14], [15]. The inaccurate location results in performance degradation of geographic routing protocols [16]–[20]. Another concern is

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the outdated location information caused by high mobility of vehicles. The naive technique to address this problem is by increasing the beacon frequency. However, this solution leads to higher channel overhead. To address this problem, future positions of vehicles have been predicted in the past studies [21], [22]. However, the prediction assumes accurate location information, which is not appropriate, particularly in realistic vehicular environments. Moreover, predicting the future location with an inaccurate location information might worsen the performance of geographical routing.

In this context, this paper proposes a Location Error Resilient Geographical Routing (LER-GR) protocol for VANETs. LER-GR reduces the impact of location error on the performance of the geographical routing protocol. It considers the location error information of the neighbouring vehicles while selecting the next forwarding vehicle (NFV). The key contributions of the paper are as follows.

- Location information correction based on the future location prediction using Kalman filter.
- NFV selection based on the least error in the location information.
- Performance evaluation in different environments including junction-based road network and a real map-based road network.

The rest of the paper is organized as follows. Section 2 qualitatively reviews geographic routing focusing on the error resilience. Section 3 describes system and location error models. The detailed description of LER-GR is presented in section 4. Simulation setup and analysis results are discussed in section 5. Section 6 concludes the paper.

2. Literature review

The impact of location error on the performance of geographical routing has been explored in the recent literature. A micro-level behaviour analysis of geographical routing protocols has been conducted for identifying the protocol error scenarios, their conditions and their bounds [18]. It has been claimed that 10% location error might result in non-recoverable routing error along with a considerable degradation in the performance. The maximum expectation within transmission range (MER) based geographical routing has been suggested to cope with a noisy location information [23]. While taking routing decisions, MER considers error probability and the information of the nodes near the border of the transmission range of the transmitting node. The conditioned mean square error ratio (CMSER) routing decision is based on the largest distance to destination, and on the smallest statistical error characteristic associated with the measured candidate nodes coordinates [24]. The energy constrained mean square error (ECMSE) [25] algorithm is an extension of CMSER. ECMSE minimises the energy expenses of sensors while being

robust to the localization errors. The aforementioned protocols do not consider mobility of nodes in location estimation.

The impact of mobility on the performance of geographical routing has been explored in [21]. The future location of vehicles has been predicted while making forwarding decisions for avoiding transmission failure to the next forwarding vehicle. However, due to the location error in measurement, the future location of the vehicles is incorrectly predicted. The location of neighbours has been predicted while choosing the next forwarding node [23]. However, imperfect location information leads to incorrect location prediction. An on-demand routing algorithm has been suggested for enhancing the robustness to the location errors based on mobility prediction in [26]. Kalman filter has been used for location correction and mobility prediction. Based on mobility prediction, nodes choose the longest lifetime route among candidate nodes. This on-demand routing algorithm is a proactive protocol which is not well suited for highly dynamic VANETs. Thus, design of geographical routing that can cope with location error in highly dynamic vehicular environments is a challenging task, in spite of the considerable attention made from both academia and industries.

3. System Model

In this section, the system models are described as the problem formulation and the mathematical derivation of location error, in the context of vehicular environment.

3.1. Problem Formulation

Consider a set of moving vehicles, denoted by V . Any two vehicles of the set can communicate only if the pair is within the transmission range of each other. The reachability can be determined using geographical location information. The vehicles measure their geographical location using on-board GPS receiver, and update it at uniform intervals of time. However, geographical locations of the vehicles measured from the GPS are not accurate. The measurement state equation, describing the relation between the actual $x_k(t_s)$ and measured positions $x'_k(t_s)$ of a vehicle V_k at any time t_s can be expressed as:

$$x'_k(t_s) = x_k(t_s) + \varepsilon_k(t_s) \quad (1)$$

where $\varepsilon_k(t_s)$ is the location error in measurement. According to the kinematics equations of motion, the future location of a vehicle in the next time stamp can be predicted as:

$$\hat{x}_k(t_s + \delta t) = x'_k(t_s) + v_k(t_s) * \delta t \quad (2)$$

where $\hat{x}_k(t_s + \delta t)$ represents the predicted location of the vehicle V_k at time $(t_s + \delta t)$, $v_k(t_s)$ is the vehicle velocity at time t_s , and δt is the sampling interval. The inaccurate location information induces incorrect future location estimate, which leads to the degradation in performance of geographic routing. As

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illustrated in Fig. 1, the future locations of the vehicles V_k and V_l are estimated based on the measured locations $x'_k(t_s)$ and $x'_l(t_s)$, respectively. By using the estimated future locations, even though V_l is inside the transmission range of V_k , it locates itself outside the transmission range in the considered scenario.

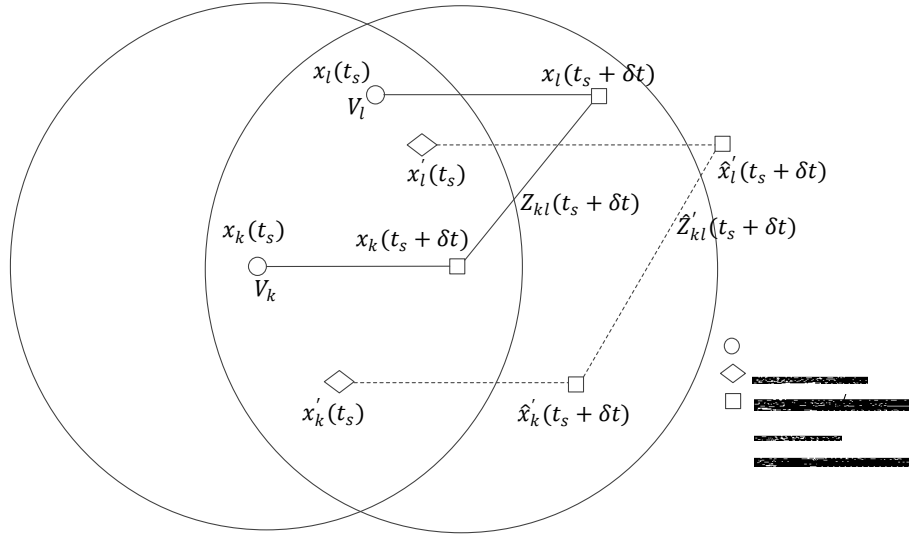


Fig. 1. The estimation of future location of neighbouring vehicles

3.2. Error Model

The traditional geographical routing protocols assume that the location information acquired from GPS is accurate. However, a GPS receiver has some inherent localization error, up to ± 10 to $30m$ [13]. The probability distribution of location error is taken as Gaussian, similar to the models in [23], [24]. In a two dimensional plane, let a relay vehicle V_k have the true location $V_k(x_k, y_k)$ and the estimated location $V_k(x'_k, y'_k)$ where $x'_k = x_k + \varepsilon_k$, $y'_k = y_k + \varepsilon_k$. The $\varepsilon_k \sim N(0, \sigma_k^2)$ is modelled as Gaussian distribution with zero mean and standard deviation σ_k . The location error of a vehicle can be defined as the difference in true and estimated location. Hence, the location error of vehicle V_k can be calculated as:

$$Z_k = \sqrt{(x_k - x'_k)^2 + (y_k - y'_k)^2} = \sqrt{\varepsilon_k^2 + \varepsilon_k^2} \quad (3)$$

where Z_k follows Rayleigh distribution, and is represented by the probability density function given by (4).

$$f(Z_k) = \frac{Z_k}{2\sigma_k^2} e^{-Z_k^2/2\sigma_k^2} \quad (4)$$

Let vehicle V_l , a candidate forwarding vehicle with true location $V_l(x_l, y_l)$ and estimated location $V_l(x'_l, y'_l)$, where $x'_l = x_l + \varepsilon_l$, $y'_l = y_l + \varepsilon_l$. Similarly, ε_l is modelled as Gaussian distribution with zero as mean and standard deviation σ_l . The ε_l can be written as $\varepsilon_l \sim N(0, \sigma_l^2)$.

The actual Euclidian distance Z_{kl} between the vehicles V_k and V_l is given by (5).

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$$Z_{kl} = \sqrt{(x_k - x_l)^2 + (y_k - y_l)^2} \quad (5)$$

The estimated Euclidian distance \hat{Z}_{kl} between the vehicles V_k and V_l is calculated as:

$$\hat{Z}_{kl} = \sqrt{(x'_k - x'_l)^2 + (y'_k - y'_l)^2} \quad (6)$$

The probability density function of \hat{Z}_{kl} follows Rice distribution, and is given by (7).

$$f(\hat{Z}_{kl}) = \frac{\hat{Z}_{kl}}{\sigma_{kl}^2} \exp\left(\frac{-(\hat{Z}_{kl}^2 + Z_{kl}^2)}{2\sigma_{kl}^2}\right) I_0\left(\frac{\hat{Z}_{kl}Z_{kl}}{\sigma_{kl}^2}\right) \quad (7)$$

where I_0 is the modified Bessel function of the first kind with zero order, and is given by (8).

$$I_0(x) = \frac{1}{\pi} \int_0^\pi \cosh(x \cos \theta) d\theta \quad (8)$$

The combined variance σ_{kl} is given by (9).

$$\sigma_{kl}^2 = \sigma_k^2 + \sigma_l^2 \quad (9)$$

The mean or first central moment of the estimated distance \hat{Z}_{kl} is given by (10).

$$E(\hat{Z}_{kl}) = \sigma \sqrt{\pi/2} L_{1/2}(-Z_{kl}^2/2\sigma_{kl}^2) \quad (10)$$

Here, $L_q(x)$ denotes the Laguerre polynomial and for the case $q = 1/2$:

$$L_{1/2}(x) = e^{x/2} \left[(1-x)I_0\left(\frac{-x}{2}\right) - xI_1\left(\frac{-x}{2}\right) \right] \quad (11)$$

and I_1 is the modified Bessel function of the first kind and order one. The second central moment, the variance of \hat{Z}_{kl} is given by (12).

$$\text{Variance} = 2\sigma_{kl}^2 + Z_{kl}^2 - \frac{\pi \sigma_{kl}^2}{2} L_{1/2}^2\left(-\frac{Z_{kl}^2}{2\sigma_{kl}^2}\right) \quad (12)$$

4. Location Error Resilient Geographical Routing

In this section, the detail of the modifications of Geographic Distance Routing (GEDIR) [27] as LER-GR is presented.

4.1. Location Prediction and correction

In this section, Kalman filter [28] is employed to predict and correct the future location of vehicles. The State vector consists of the true location and the true velocity of a vehicle at time t_s and is represented as $X_k(t_s) = \begin{bmatrix} x_k(t_s) \\ v_k(t_s) \end{bmatrix}$. The measurement vector of the vehicle consists of the measured location and the measured velocity and is represented as $X'_k(t_s) = \begin{bmatrix} x'_k(t_s) \\ v'_k(t_s) \end{bmatrix}$. The relation between the true location $x_k(t_s)$ and the estimated location $x'_k(t_s)$ is given by Eq. (1). The relation between $v_k(t_s)$ and $v'_k(t_s)$ can be

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calculated as follows: In the time $\delta t = t_s - t_{s-1}$, a vehicle k moves from $x(t_{s-1})$ to $x(t_s)$ such that $x(t_s) = x(t_{s-1}) + \delta t v(t_s)$. Hence the measured velocity v'_k can be expressed as given by (13).

$$v'_k(t_s) = \frac{x'_k(t_s) - x'_k(t_{s-1})}{\delta t} = v_k(t_s) + \frac{\varepsilon_k(t_s) + \varepsilon_k(t_{s-1})}{\delta t} = v_k(t_s) + \frac{\varepsilon_k(t_s, t_{s-1})}{\delta t} \quad (13)$$

Considering constant velocity of vehicles, i.e., $v_k(t_s) = v_k(t_{s-1})$, during time interval δt , the process equation which predicts the state of the system can be written as given by (14).

$$X_k(t_{s+1}) = H_k(t_s) * X_k(t_s) \quad (14)$$

where $H_k(t_s) = \begin{bmatrix} 1 & \delta t \\ 0 & 1 \end{bmatrix}$ represents state transition matrix. The measurement equation of Kalman filter is represented as given by (15).

$$X'_k(t_s) = F_k(t_s) * X_k(t_s) + E_k(t_s) \quad (15)$$

where $F_k(t_s) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ represents measurement matrix and $E_k(t_s) = \begin{bmatrix} \varepsilon_k(t_s) \\ \frac{1}{\delta t} \varepsilon_k(t_s, t_{s-1}) \end{bmatrix}$. The unknown state

$X_k(t_{s+1})$ can be estimated recursively using estimated values $X'_k(t_s)$ at time t_s . An estimate of the state $X_k(t_s)$ predicted at time (t_{s-1}) is known in advance. The initial state $\hat{X}_k(t_0)$ is fixed on the basis of the measured information in the beginning. For simplicity, $F_k(t_s)$, $H_k(t_s)$, and $K_k(t_s)$ is written as F_k , H_k , and K_k respectively.

The *a priori* estimate vector $X_k^-(t_s)$ is formulated as expressed by (16).

$$X_k^-(t_s) = H_k * \hat{X}_k(t_{s-1}) \quad (16)$$

and the *a priori* state covariance matrix $P_k^-(t_s)$ is expressed as given by (17).

$$P_k^-(t_s) = H_k * P_k(t_s) * F_k^T \quad (17)$$

The *a posteriori* estimate $\hat{X}_k(t_s)$ can be calculated as expressed by (18).

$$\hat{X}_k(t_s) = X_k^-(t_s) + K_k * (X'_k(t_s) - F_k * X_k^-(t_s)) \quad (18)$$

where the Kalman gain K_k is expressed as given by (19).

$$K_k = P_k^-(t_s) * F_k^T * (F_k * P_k^- * F_k^T + R_k)^{-1} \quad (19)$$

Here, R_k represents the measurement noise covariance, and is estimated by taking some off-line sample measurements prior to the operation of the Kalman filter. The *a posteriori* estimation error covariance matrix $P_k(t_s)$ is expressed as given in (20).

$$P_k(t_s) = (I - K_k * F_k) * P_k^-(t_s) \quad (20)$$

The location of a vehicle is recursively predicted using the equations (16) to (20). The location prediction process is summarized in Fig. 2.

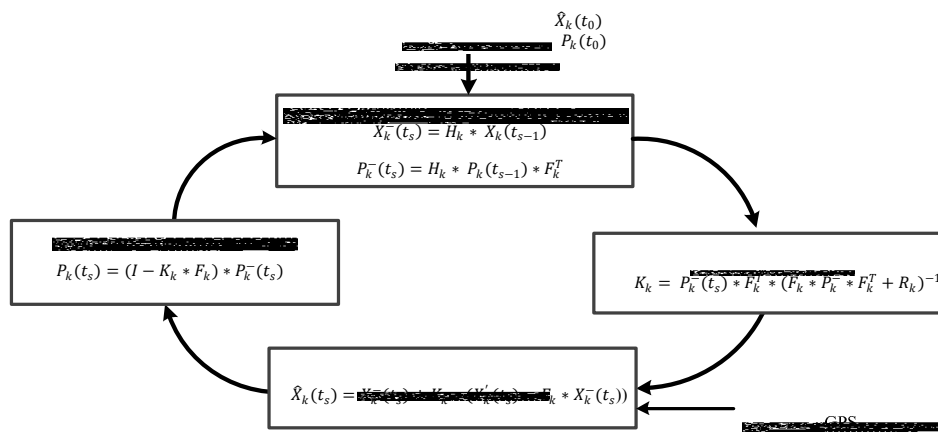


Fig. 2. The location prediction process using Kalman filter

4.2. Mean Square Error Calculation using Predicted Location

Mean Square Error (MSE) measures the difference between the predicted value and its actual value at time t . The smaller the MSE, the closer the predicted value to the actual value. The calculation is similar to CMSER but future (predicted) locations of vehicles are used instead of current locations. The source vehicle V_k calculates MSE associated with each neighbouring vehicle V_l as expressed by (21).

$$MSE(\hat{Z}_{kl}) = E(\hat{Z}_{kl} - Z_{kl})^2 = E(\hat{Z}_{kl}^2) - 2 * Z_{kl} * E(\hat{Z}_{kl}) + (Z_{kl})^2 \quad (21)$$

$E(\hat{Z}_{kl})$ is calculated using (10) and $E(\hat{Z}_{kl}^2)$ is calculated as given by (22)

$$E(\hat{Z}_{kl}^2) = E(\hat{x}_k^2 - 2 * \hat{x}_k * \hat{x}_l + \hat{x}_l^2) + E(\hat{y}_k^2 - 2 * \hat{y}_k * \hat{y}_l + \hat{y}_l^2) \quad (22)$$

Since, $E(\hat{x}_k^2) = x_k^2 + \sigma_k^2$, $E(\hat{y}_k^2) = y_k^2 + \sigma_k^2$, $E(\hat{x}_l^2) = x_l^2 + \sigma_l^2$, and $E(\hat{y}_l^2) = y_l^2 + \sigma_l^2$, thus,

$$E(\hat{Z}_{kl}^2) = 2 * \sigma_k^2 + 2 * \sigma_l^2 + x_k^2 + x_l^2 + y_k^2 + y_l^2 - 2 * x_k * x_l - 2 * y_k * y_l \quad (23)$$

Since the actual parameters Z_{kl} , x_k , x_l , y_k , and y_l are not known, calculations are performed using predicted coordinates.

4.3. Next Forwarding Vehicle Selection

After obtaining the information about neighbouring vehicles, source vehicle V_k creates its routing table, and evaluates objective function associated with each neighbouring vehicle V_l as expressed by (24)

$$OF_{kl} = MSE(\hat{Z}_{kl}) * Y_{lD} \quad (24)$$

where, Y_{lD} represents the distance between V_l and the destination vehicle. The source vehicle V_k selects a neighbour vehicle as NFV (V_{NF}) with minimum OF_{kl} . It can be expressed as given by (25).

$$V_{NF} = \text{argmin}(OF_{kl}) \quad (25)$$

A balance is attained between the shortest distance towards the destination and the smallest error in the NFV location by selecting the vehicle with minimum OF_{kl} . If there are two or more vehicles with the same

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distance to the destination, a vehicle with lower MSE is preferred as NFV. Also, if more than one vehicles have the same statistical error, then a vehicle with lesser distance to the destination is preferred as NFV.

4.4 Summary of LER-GR

LER-GR considers two metrics to select NFV including MSE of the distance between the source vehicle and the candidate NFV, and the distance between the candidate NFV and the destination vehicle. The sender vehicle, first sends modified beacon packet to each neighbouring vehicle (see Table 1). The source or sender vehicle updates its routing information table using the beacon messages received from its neighbours. Then the sender vehicle executes the location prediction and correction algorithm as discussed in section 4.1. MSE for each neighbouring vehicle is calculated using predicted location as explored in section 4.2. The next forwarding vehicle selection criteria is discussed in section 4.3.

Table 1. The format of modified beacon message presented as a single row table

<i>V-ID</i>	<i>X-Coordinate</i>	<i>Y-Coordinate</i>	<i>V-Velocity</i>	<i>Timestamp</i>	<i>Location Error Info</i>
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4.5 Complexity Analysis

The complexity of the proposed routing protocol can be analysed in terms of storage and computation complexity. Considering that a vehicle's on-board unit (OBU) has sufficient space, the storage complexity is insignificant. Therefore, only computation complexity is the major component in the complexity analysis of the proposed routing protocol. The time complexity of the LER-GR is of the order of $O(N_{nv} \cdot n^3)$, where N_{nv} is the number of neighbouring vehicles of a sender vehicle, and n indicates the dimension of the state variable in Kalman Filter. The time complexity of the proposed routing protocol is because of the computation required to predict the future location of the neighbouring vehicles using Kalman filter and some additional computations for calculating MSE and objective function. However, the latter does not change the worst-case time complexity or order of LER-GR protocol, considering finite number of neighbouring vehicles. The algorithm has only one prediction variable, therefore the running time of the location prediction algorithm does not exceed the sampling interval of the Global Navigation Satellite system (GNSS) or the in-vehicle Inertial Navigation System (INS), considering sufficient processing capacity of vehicles.

5. Performance Evaluation

In this section, the performance of the proposed protocol is comparatively evaluated with those of the state-of-the-art protocols in the presence of location error. The details of the simulation setup and the comparative analysis of results are discussed in the following sections.

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5.1 Simulation Setup

A detailed simulation study is carried out in network simulator NS-2 with the help of a realistic Mobility model generator for Vehicular network (MOVE). The mobility traffic traces generated are used as input to drive the network simulator. Two types of scenarios are considered for simulation: road based and map based. In the road based scenario, a 4 X 4 grid road network is used as a simulation area. There are four horizontal and four vertical roads crossing each other, and thus, make sixteen junction points at equal distances. Also, each road has double lanes. Map based scenario is discussed in section 5.3. Table 2 shows the complete list of simulation parameters used to configure the simulation scenarios. The parameters were heavily influenced by the works of [29]. Considering 95% confidence interval in the performance evaluations, the simulation results are obtained by performing twenty (20) simulation repetitions for every scenario.

The two metrics used for assessing the performance include throughput and normalized routing load. The throughput can be defined as the amount of data delivered successfully from the source vehicle to the destination vehicle per unit time in presence of location error. The throughput is measured in terms of bits per second. It can be calculated as expressed by (26).

$$\text{Throughput (kbps)} = \frac{\sum_{i=1}^{20} (N_i^{ps} - N_i^{pl})}{20} \times \frac{512}{1024 \times 600} \quad (26)$$

where N_i^{ps} represents the number of packets sent in i^{th} simulation and N_i^{pl} represents the number of packets lost due to location error in i^{th} simulation. Normalized routing load (NRL) refers to the total number of routing packets transmitted by a routing protocol for successful delivery of a data packet. It can be calculated as expressed by (27).

$$\text{Normalized routing load} = \frac{\sum_{i=1}^{20} (N_i^{cp} - N_i^{ddp})}{20} \times 100 \quad (27)$$

where N_i^{cp} represents the number of control packets required for network initialization with location error in i^{th} simulation and N_i^{ddp} represents the number of duplicate data packets sent due to the location error in i^{th} simulation until the reception of the particular data packet. The performance metrics are measured for increasing density, velocity and standard deviation of location error of the vehicles. The performance of LER-GR protocol is compared with SLD-GEDIR [29] protocol apart from traditional GEDIR. In SLD-GEDIR, the choice of NFV depends on segment vehicles, one-hop link quality and degree of connectivity. For a complete comparison and a more appropriate evaluation, GEDIR and SLD-GEDIR are modified to simulate with inaccurate locations.

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Table 2. Simulation parameters

Parameters	Values	Parameters	Values	Parameters	Values
Simulation area	1500 X 1000 m ²	Trans. Protocol	UDP	Frequency	5.9 GHz
Vehicles	10 – 500	Interface queue	50	MAC data rate	5 Mbps
Velocity	5 – 60 km/hr	Channel type	Wireless	Query period	3 sec
Trans. Range	250 m	Prop. Model	Shadowing	Hello timeout	1 sec
Packet sender	30	Antenna model	Omni directional	Loc. error stand. deviation	0 – 40 m
Network traffic	CBR (512 bytes, 6 pps)	Phy/Mac	IEEE 802.11p	Simulation time	600 sec

5.2 Analysis of Results: Road-based Scenario

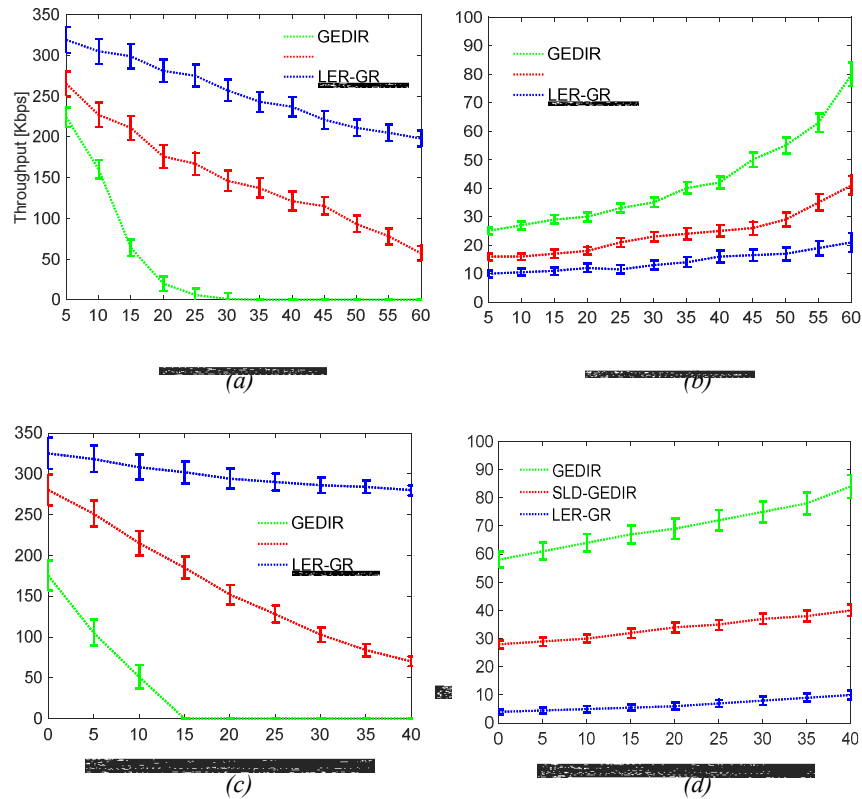


Fig. 3. Road-based results: impact of vehicle velocity on, (a) throughput, (b) normalized routing load, and impact of location error on, (c) throughput (d) normalized routing load

Fig. 3(a) show the impact of velocity of vehicles on the throughput of LER-GR and the state-of-the-art protocols. It is evident from the results that the throughput of LER-GR is higher as compared to the other protocols for the considered range of velocity of vehicles. Additionally, the throughput of LER-GR decreases slowly with the increase in velocity of vehicles as compared to the other protocols. This can be attributed to the fact that the location resilience capability of LER-GR reduces link failure in forwarding path, resulting in higher throughput and slower decrement. As location error is not considered in the NFV

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selection, throughput of the state-of-the-art protocols are lower. The throughput of SLD-GEDIR is higher as compared to GEDIR due to the consideration of the link quality parameter in NFV selection, which is able to reduce the impact of location error up to some level.

In Fig. 3(b), results show the impact of velocity of vehicles on the normalized routing load of LER-GR and state of-the-art protocols. The normalized routing load of all the considered protocols increase with increase in the velocity of vehicles. This can be reasoned to the fact that link failure will be frequent with the increase in the velocity of the vehicles. This increases data packet loss and thus, more routing packets will be generated to transmit data packets from the source vehicle to the destination vehicle. Among the considered protocols, GEDIR has the highest normalized routing load and LER-GR protocol has the lowest, followed by SLD-GEDIR. The high normalized routing load of GEDIR is because of the lack of mechanism to deal with location inaccuracy. The normalized routing load of SLD-GEDIR protocol is lower than GEDIR because of the consideration of velocity in its NFV selection logic. LER-GR protocol has the lowest normalized routing load. The reason being that LER-GR protocol exploits the future location of the vehicles for routing decisions to alleviate the impact of mobility. LER-GR protocol uses statistical error characteristics of location error of neighbouring vehicles in NFV selection mechanism.

Fig. 3(c) shows the impact of standard deviation of location error on the throughput of LER-GR and the state-of-the-art protocols. It can be noticed that LER-GR obtains the highest throughput. This is because of the fact that LERGR takes into consideration the statistical error characteristics of forwarding candidates in NFV selection logic. To alleviate the effect of mobility, the future location of vehicles is predicted and corrected by Kalman filter. A vehicle with the minimum variance of location error and the maximum progress towards the destination, is selected as NFV. Besides, SLD-GEDIR achieves better results as compared to GEDIR due to the use of link quality parameter resulting in lower packet losses. Fig. 3(d) shows the impact of standard deviation of location error on normalized routing load of LER-GR and considered state-of-the-art protocols. The normalized routing load of the state-of-the-art protocols is higher as compared to the proposed protocol. GEDIR takes the forwarding decision by only considering the distance to the destination. This makes it prone to location error and increases the normalized routing load. In the case of SLD-GEDIR, consideration of the link quality parameter in NFV selection logic makes it experience lesser routing overhead. The behaviour of the LER-GR mainly depends on how the selection of NFV is designed. LER-GR uses location error of vehicles in NFV selection logic. This makes LER-GR location error resilient, resulting in less number of routing packets required for successful delivery of packets.

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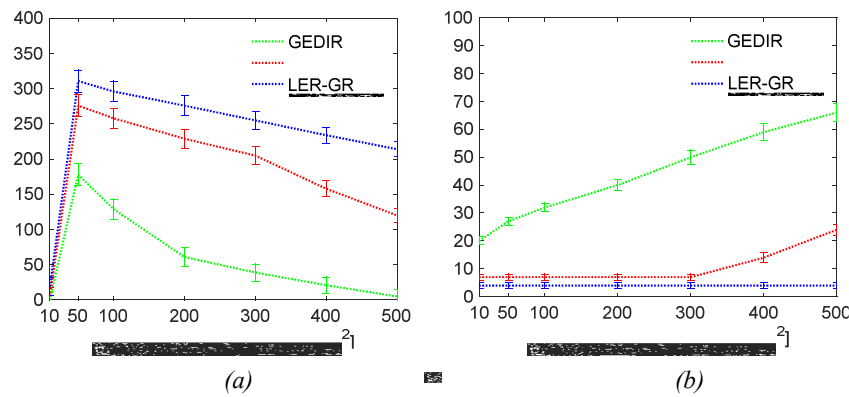


Fig. 4. Road-based results: impact of vehicle density on (a) throughput, (b) normalized routing load

The impact of vehicle density, i.e., 10 – 500 vehicles/1500 × 1000 m², on the network throughput is shown in Fig. 4(a). For all the considered protocols, increase in the throughput is observed with the increase in vehicle density upto a certain density but then it starts decreasing. Increase in the throughput with increasing vehicle density is obvious as all the considered protocols starts to find an appropriate forwarding vehicle to transmit data packets. A decrease in throughput with increasing number of vehicles can be attributed to the following reasons. Firstly, when the vehicle density increases, the number of collisions increase as more vehicles are contending to access the channel. Secondly, the probability of finding a vehicle near the border of transmission range of a sender vehicle increases as the vehicle density increases. The vehicles near to the border of transmission range have the highest possibility of going out of the range during transmission. Therefore, probability of link failure increases with increase in vehicle density. SLD-GEDIR experiences higher throughput than GEDIR because of the consideration of the link quality parameter while selecting NFV. The degradation in throughput of LER-GR protocols with the increase in vehicle density is only because of MAC collisions. In the presence of location error, a better capability of handling location error is observed in LER-GR. This significantly reduces the packet loss, resulting in a higher throughput as compared to the other considered protocols.

Fig. 4(b) shows the impact of vehicle density on the normalized routing load of the network. As evident from the results, the normalized routing load of LER-GR protocol is stable. In case of the state-of-the-art protocols, normalized routing load increases with increase in vehicle density. This can be attributed to the reason that the proposed protocol takes into consideration the statistical error characteristics of the forwarding candidates in NFV selection logic, making it location error resilient. The vehicle with the minimum variance of location error and making the maximum progress towards destination, is selected as NFV. The normalized routing load of SLD-GEDIR is lower in comparison with GEDIR protocol, as SLD-GEDIR takes into account the quality of each link while selecting NFV. The increase in normalized

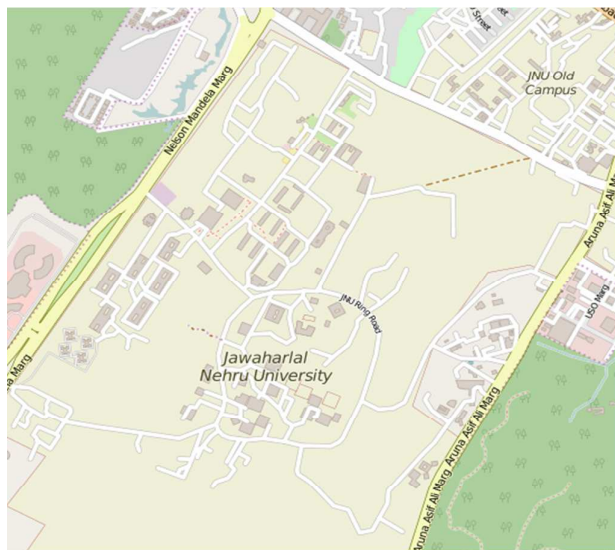
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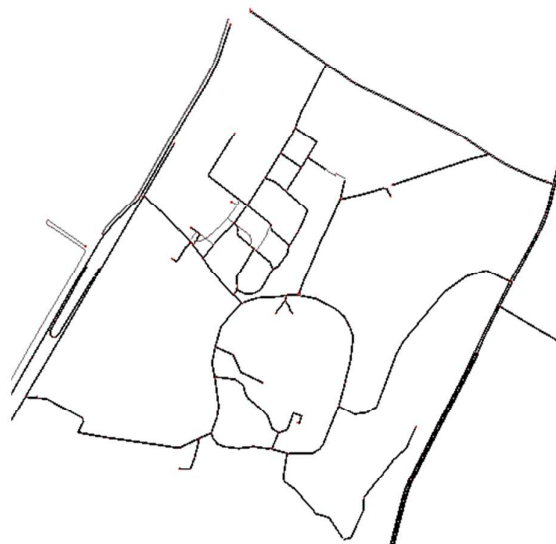
routing load of GEDIR with increasing vehicle density is due to the absence of a better forwarding vehicle selection strategy.

5.3 Analysis of Results: Map-based Scenario

In the map-based scenario, the real road network of Jawaharlal Nehru University (JNU), New Delhi, India is used as the simulation area (see Fig. 5(a) and (b)). The map is retrieved from the Open Street Map (OSM) [30] and a road traffic scenario is created with the help of MOVE and SUMO. All the other parameters of the simulation are similar to what is considered in the road-based scenario.



(a)



(b)

Fig. 5. Real road network of JNU, New Delhi, India (a) Open Street View (b) Imported view in MOVE

Fig. 6(a), (b) and (c) show the impact of velocity, standard deviation of location error, and vehicle density on the throughput of LER-GR and the state-of-the-art protocols; respectively. Although, the pattern of the performance for each of the metrics considered is similar to what is observed in the road-based results, the ranges of the throughput being offered by the protocols make the results quite significant. Specifically, an approximately 50 Kbps higher throughput for LER-GR is observed compared to what it is observed in the road-based scenario. For GEDIR and SLD-GEDIR, approximately 40 Kbps lower throughput is observed compared to what is observed in the road-based scenario. The higher throughput in the map-based scenario offered by the proposed protocol clearly states that the adaptation of LER-GR in a realistic scenario is quite beneficial as compared to the degraded performance of the state-of-the-art protocols. This adaptation is because of the better location prediction capability of LER-GR in case of more number of junctions

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between the source and the destination vehicles, which is quite clearly evident in the map-based scenario as compared to the road-based scenario where the number of junctions is limited to 16.

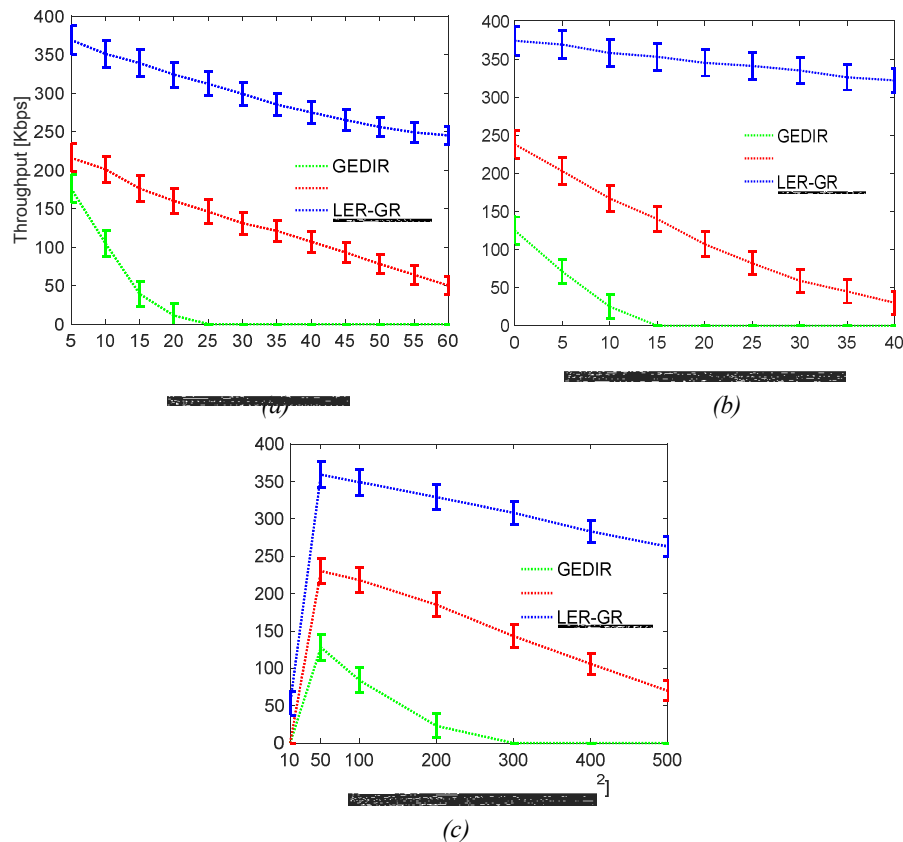


Fig. 6. Map-based results: impact of (a) vehicle velocity, (b) location error, and (c) vehicle density on throughput

The performance of LER-GR and the state-of-the-art protocols in terms of the normalized routing load metric with increasing velocity, standard deviation of location error, and vehicle density is shown in Fig. 7(a), (b) and (c); respectively. Not surprisingly, the pattern of the performance of the LER-GR and the considered protocols is similar to the road based results. However, there is a slight improvement in the performance of LER-GR whereas GEDIR and SLD-GEDIR perform badly in realistic scenario. Approximately 5% -10% reduction of normalized routing load for LER-GR is observed than what it is observed in the road-based scenario. For GEDIR and SLD-GEDIR, approximately 5% – 10% increment in normalized routing load is observed in comparison with the road-based scenario. Overall, it can be said that error in location information obtained from GPS is inevitable. In such a case, a routing protocol which also takes this error into account, like LER-GR, enhances the overall performance of the network.

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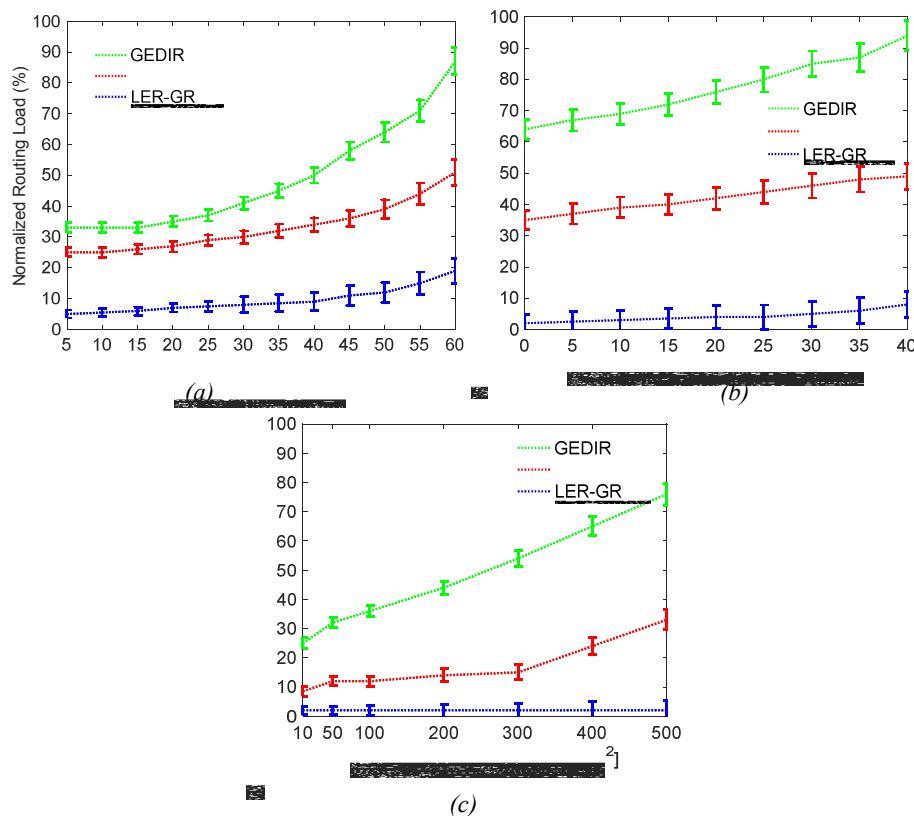


Fig. 7. Map-based results: impact of (a) vehicle velocity, (b) location error, and (c) vehicle density on normalized routing load

5.4 Comparative Analysis of Road-based and Map-based Results

In this section, the simulation results obtained after considering two different vehicular traffic scenario, are tabulated for intensifying the benefits of the LER-GR protocol in a realistic map-based scenario (see Table 3). Minimum, maximum and average are the three metrics considered for the comparative analysis. It can be clearly observed that the performance of LER-GR improves significantly in the map-based vehicular traffic scenario whereas the performance of GEDIR and SLD-GEDIR degrades. In case of the road-based scenario, the throughput of LER-GR is lower as compared to the map-based scenario. Also, the normalized routing load of LER-GR, is always higher in case of the road based scenario. The high throughput and the low normalized routing load of LER-GR in the map-based scenario in comparison to the road-based scenario is because of the higher number of junctions between the source and the destination vehicles in the map-based scenario, resulting in a better location prediction. The performance degradation of SLD-GEDIR and GEDIR in terms of lower throughput and higher normalized routing load in map-based scenario is because of the fact that both the protocols lacks the capability to handle location error due to vehicle mobility.

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Table 3. Comparative assessment of road-based and map-based simulation results

		Protocols and traffic scenario		LER-GR		SLD-GEDIR		GEDIR	
		Metrics		Road	Map	Road	Map	Road	Map
Vehicle Velocity	Throughput	Minimum	198	245	57	50	0	0	
		Maximum	319	369	265	216	224	176	
		Average	254.25	297.42	149.42	128.58	39.58	27.58	
	Normalized Routing Load	Minimum	10	5	16	25	25	33	
		Maximum	21	19	41	51	80	87	
		Average	14.29	9.46	24.25	33.17	42.42	48.92	
Vehicle Density	Throughput	Minimum	19	53	6	0	0	0	
		Maximum	311	359	276	230	178	128	
		Average	192.35	236.9	149.85	116.85	64.25	33.65	
	Normalized Routing Load	Minimum	4	2	7	8.5	20	25	
		Maximum	4	2	24	33	66	76	
		Average	4	2	8.95	14.35	36.15	41.4	
Standard Deviation of Location Error	Throughput	Minimum	280	322	70	30	0	0	
		Maximum	325	374	280	238	175	125	
		Average	298.56	347	163.11	119	36.78	24.56	
	Normalized Routing Load	Minimum	4	2	28	35	58	64	
		Maximum	10	8	40	49	84	94	
		Average	6.56	4.22	33.67	42.22	69.78	77.11	

6. Conclusion

In this paper, a location error resilient geographical routing (LER-GR) protocol is presented. From the design, implementation and performance evaluation of LER-GR, the following conclusions have been made. Rayleigh distribution based location error calculation, and Kalman filter based location prediction and correction of LER-GR protocol reduces the impact of location error on the performance of geographic routing protocol. The throughput of LER-GR is higher and the normalized routing load is lower in comparison with SLD-GEDIR and GEDIR in the self-modelled junction-based road network. The performance of LER-GR improves in the real map-based road network environment whereas the performance degrades for SLD-GEDIR and GEDIR in terms of throughput and network load considering increasing velocity, density and standard deviation of location error. In future, authors will explore the cooperative positioning techniques for enhancing the accuracy of GPS-assisted localization in VANETs.

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References

- [1] Wan, J., Liu, J., Shao, Z., *et al.*: 'Mobile Crowd Sensing for Traffic Prediction in Internet of Vehicles' *Sensors*, 2016, 16, (1), p. 88.
- [2] Kaiwartya, O., Abdullah, A.H., Cao, Y., *et al.*: 'Internet of Vehicles: Motivation, Layered Architecture, Network Model, Challenges and Future Aspects' *IEEE Access*, 2016, 4, pp. 5356–5373.
- [3] Stefan, R.: 'Theory and Practice of Geographic Routing', in 'Ad Hoc and Sensor Wireless Networks: Architectures, Algorithms and Protocols' (Bentham Science Publishers, 2012), pp. 69–88.
- [4] Sheet, D.K., Kaiwartya, O., Abdullah, A.H., *et al.*: 'Location information verification using transferable belief model for geographic routing in vehicular ad hoc networks' *IET Intelligent Transport Systems*, 2016, (September).
- [5] Zhao, J., Cao, G.: 'VADD: Vehicle-assisted data delivery in vehicular Ad hoc networks' *IEEE Transactions on Vehicular Technology*, 2008, 57, (3), pp. 1910–1922.
- [6] Gong, J., Xu, C.-Z., Holle, J.: 'Predictive Directional Greedy Routing in Vehicular Ad hoc Networks', *Proc. Int. Conf. on Distributed Computing Systems Workshops (ICDCSW'07)* (IEEE, 2007)
- [7] Jerbi, M., Senouci, S.-M., Meraihi, R., *et al.*: 'An Improved Vehicular Ad Hoc Routing Protocol for City Environments', *Proc. IEEE Int. Conf. Communications* (IEEE, 2007), pp. 3972–3979
- [8] Brahmi, N., Boussedjra, M., Mouzna, J., *et al.*: 'Adaptative movement aware routing for vehicular ad hoc networks', *Proc. Int. Conf. Wireless Communications and Mobile Computing Connecting the World Wirelessly - IWCMC '09'* (ACM Press, 2009), pp. 1310–1315
- [9] Menouar, H., Lenardi, M., Filali, F.: 'Movement Prediction-Based Routing (MOPR) Concept for Position-Based Routing in Vehicular Networks', *Proc. IEEE 66th Vehicular Technology Conf.* (IEEE, 2007), pp. 2101–2105
- [10] Liu, J., Wan, J., Wang, Q., *et al.*: 'A survey on position-based routing for vehicular ad hoc networks' *Telecommunication Systems*, 2016, 62, (1), pp. 15–30.
- [11] Yan, T., Wang, G.: 'Collecting vehicle trajectory through message dissemination' *Ad-Hoc & Sensor Wireless Networks*, 2015, 29, (1–4), pp. 153–176.
- [12] Nebot, E.: 'Navigation System Design'. University of Sydney, Australia, 2005
- [13] Boukerche, A., Oliveira, H.A.B.F., Nakamura, E.F., *et al.*: 'Vehicular Ad Hoc Networks: A New Challenge for Localization-Based Systems' *Computer Communications*, 2008, 31, (12), pp. 2838–2849.
- [14] Liu, J., Wan, J., Wang, Q., *et al.*: 'A time-recordable cross-layer communication protocol for the positioning of Vehicular Cyber-Physical Systems' *Future Generation Computer Systems*, 2016, 56, pp. 438–448.
- [15] Cao, Y., Wang, T., Kaiwartya, O., *et al.*: 'An EV Charging Management System Concerning Drivers' Trip Duration and Mobility Uncertainty' *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 2016, 99, pp. 1–12.
- [16] Witt, M., Turau, V.: 'The Impact of Location Errors on Geographic Routing in Sensor Networks', *Proc. Int. Conf. Wireless and Mobile Communications (ICWMC'06)* (IEEE, 2006).
- [17] Kim, Y., Lee, J., Helmy, A.: 'Modeling and Analyzing the Impact of Location Inconsistencies on Geographic Routing in Wireless Networks' *Mobile Computing and Communications Review*, 2004, 8, (1), pp. 48–60.
- [18] Seada, K., Helmy, A., Govindan, R.: 'On the Effect of Localization Errors on Geographic Face Routing in

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- Sensor Networks', Proc. 3rd Int. Symp. Information processing in sensor networks (2004), pp. 71–80.
- [19] Oliveira, H.A.B.F., Nakamura, E.F., Loureiro, A.A.F., Boukerche, A.: 'Error Analysis of Localization Systems for Sensor Networks', Proc. Int. Workshop on Geographic Information Systems - GIS '05' (2005), pp. 71–78.
- [20] Peng, B., Mautz, R., Kemp, A.H., *et al.*: 'On the effect of localization errors on geographic routing in sensor networks', Proc. IEEE Int. Conf. Communications' (2008), pp. 3136–3140.
- [21] Son, D., Helmy, A., Krishnamachari, B.: 'The Effect of Mobility-Induced Location Errors on Geographic Routing in Mobile Ad Hoc and Sensor Networks: Analysis and Improvement Using Mobility Prediction' IEEE Transactions on Mobile Computing, 2004, 3, (3), pp. 233–245.
- [22] Haipeng, Y., Pengbo, S., Ruizhe, Y., *et al.*: 'Dynamic Spectrum Management with Movement Prediction in Vehicular Ad Hoc Networks' Ad-Hoc & Sensor Wireless Networks, 2016, 32, (1–2), pp. 79–97.
- [23] Kwon, S., Shroff, N.B.: 'Geographic routing in the presence of location errors' Computer Networks, 2006, 50, pp. 2902–2917.
- [24] Popescu, A.M., Salman, N., Kemp, A.H.: 'Geographic Routing Resilient to Location Errors' IEEE Wireless Communications Letters, 2013, 2, (2), pp. 203–206.
- [25] Popescu, A.M., Salman, N., Kemp, A.H.: 'Energy efficient geographic routing robust against location errors,' IEEE Sensor Journal, 2014, vol. 14, no. 6, pp.1944-1951.
- [26] Vu, T.K., Kwon, S.: 'Mobility-Assisted on-Demand Routing Algorithm for MANETs in the Presence of Location Errors' The Scientific World Journal, 2014, pp. 1–11.
- [27] Stojmenovic, I., Lin, X.: 'Loop-Free Hybrid Single-Path / Flooding Routing Algorithms with Guaranteed Delivery for Wireless Networks' IEEE Transactions on Parallel and Distributed Systems, 2001, 12, (10), pp. 1023–1032.
- [28] Welch, G., Bishop, G.: 'An Introduction to the Kalman Filter' UNC-Chapel Hill, TR95-041, 2006, pp. 1–16.
- [29] Kaiwartya, O., Kumar, S., Lobiyal, D., *et al.*: 'Performance Improvement in Geographic Routing for Vehicular Ad Hoc Networks' Sensors, 2014, 14, (12), pp. 22342–22371.
- [30] 'Open Street Map', <http://www.openstreetmap.org>