Advances in Engineering Software 173 (2022) 103250

Contents lists available at ScienceDirect

Advances in Engineering Software

journal homepage: www.elsevier.com/locate/advengsoft

Research paper

A novel extended Kalman filter-based optimized routing approach for IoV environment

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ARTICLE INFO

Keywords:
IoV
V2V
Routing
Prediction

ABSTRACT

The development of intelligent transportation system has divulged towards traffic management, planning and control that requires precise neighboring vehicle location anticipation for information transmission. The crucial problem is to maintain QoS parameters in high speed and varying vehicular topology environment. The paper presents a novel EK-PGRP (Extended Kalman filter- Predictive Geographic Routing Protocol) routing approach to anticipate neighbor location and to select the propitious neighbor for advancing packets from source to destination vehicle using extended Kalman filter for real-time V2V communication in both urban and highway vehicular environment. This is acquired according to spatial and temporal movement attributes; every vehicle has an anticipation model to anticipate its own and neighboring vehicle mobility. Moreover, if LMP (Local Maximum Problem) state is encountered, i.e., where a vehicle is unable to locate any neighbor nearer to destination than itself to forward an information packet; then it uses predictive prediction algorithm to overcome that state. The precision, robustness and coherence attributes of the proposed routing approach are illustrated via extensive simulations. EK-PGRP is contrasted with K-PGRP (Kalman filter- Predictive Geographic Routing Protocol), PGRP (Predictive Geographic Routing Protocol) and GPSR (Greedy Perimeter Stateless Routing) routing protocols and results demonstrate that EK-PGRP outperformed most of the simulation cases and attained the minimum location error while ameliorating prediction accuracy of the vehicles in vehicular environment. The simulations were performed on MATLAB R2018a along with traffic simulator SUMO.

1. Introduction

Various analyses have shown that in-advance notification to the drivers and commuters regarding unexpected risks may decrease nearly 60% of the vehicle fatalities [5]. In order to upgrade the street security, traffic stream control, traffic observing and infotainment administrations, vehicular communication has engrossed concern in the automotive field [4,18]. Internet of Vehicles (IoV) is proposed as a global network of wireless access technology accredited vehicles comprising Internet and provides5 types of communication amid vehicles i.e., V2V (Vehicle to Vehicle), V2I (Vehicle to Infrastructure), V2S (Vehicle to Sensors), V2R (Vehicle to Roadside unit) and V2P (Vehicle to Personal devices). Each kind of communication in IoV wields different WAT (Wireless Access Technology) standard to exchange information. V2V communication wields WAVE (IEEE 802.11p) technology [11]. Routing information amid vehicles in such a dynamic network is one of the rising issues these days. Routing protocol is a way through which source vehicle transfers information to the destination vehicle. Geographic Routing / Georouting is a routing principle which bank upon the geological location of the vehicle unlike topology-based routing protocols which rely on building and perpetuating end to end connectivity in order to advance hello packet from source to destination vehicle by finding appropriate neighboring vehicles [3]. It is contemplated in georouting protocols that vehicle wields GPS to know its own location and based on the location of destination and neighboring vehicles, the routing choice is made. Thus, the precise information of vehicle location is essential. Although, georouting renders best route selection for vehicles in V2V environment but it has few constraints. PGRP [13] as a recent georouting protocol wields predictive greedy forwarding approach in order to anticipate near future location of neighboring vehicles and encounter many constraints. Firstly, PGRP wields local information by discerning one-hop neighbors. Therefore, every vehicle advances the packet which is accurate from local point of view, i.e., follows greedy approach and this conventional greedy concept is applied on the future predicted positions. Thus, at every instant, PGRP fails to provide a global optimum solution as it discerns one- hop neighbors

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https://doi.org/10.1016/j.advengsoft.2022.103250
Received 16 July 2022; Received in revised form 12 August 2022; Accepted 20 August 2022
Available online 8 September 2022

based on local information only. Secondly, in order to anticipate neighbor vehicle location, the present node (i.e., vehicle) in PGRP assign weight to neighboring vehicles based on direction and distance parameters only and velocity parameter is not considered which can degrade the connectivity of two vehicles in high mobility environment leading to high packet loss and degrading throughput. Thirdly, PGRP is applied in both urban and highway environment and instead of applying a real urban environment, it incorporates a simple grid layout for urban environment. Although, PGRP predicts neighbor location but lacks in precise location prediction of neighboring vehicle and also QoS parameters degrades due to aforesaid constraints. Thus, to upgrade the connectivity in georouting protocols and to overcome the shortcomings of PGRP protocol and state of the art geographic routing protocols mentioned above, this paper presents hybrid protocol i.e., EK-PGRP, which anticipate neighbor location and information forwarding approach using extended Kalman filter [12] for real-time V2V communication in both urban and highway vehicular environment. A novel EK-PGRP (Extended Kalman filter based PGRP) solution for neighbor vehicle prediction is provided through combination of hello protocol with predicting vehicular mobility through extended Kalman filter.

2. Related work

In the literature, most works focus on the routing mechanism. In order to preserve network performance in critical circumstances, as in a VANET, geographical routing protocols [3] are the most appropriate, which are a class of routing protocols that use location of forwarding nodes to route packets. An advantage of VANET is the accessibility of its navigation systems that allows each vehicle to be aware of the geographic location of its neighbors. It is a challenging task to develop an efficient VANET routing protocol that can handle connectivity in geographic routing and route recovery as well as having a forwarding method in highway and urban vehicular environment [26]. Although, georouting renders best route selection for vehicles in V2V environment but it has few constraints which are illustrated below:

(a) Selecting optimum forwarder: Georouting forwarding criteria is based on the information accessible from local sources i.e., the finest one hop neighbor disseminates the information packet. Thus, choosing he finest forwarder plays a significant task because the network situation is initially not known [3].
(b) Out of Bound Problem (OBP): Most georouting protocols in VANET like GPSR, CAR, GPCR etc. contemplates those vehicles are static and hence cannot anticipate the near future location of neighboring vehicles [3,13,19]. But in real world environment vehicles have dynamic velocity, which results in OBP in vehicles. Fig. 1 illustrates OBP in which, vehicle X is a source vehicle and has neighboring vehicles Y and Z in its transmission range. X wants to forward hello packet to moving destination vehicle D. All vehicles are moving at different high speed. At time t, Y and Z are having the hello packet and Z is nearest to D. At time t_1, the packet is forwarded to Z but Z goes out of bound of X i.e., not in the transmission range of X due to high speed and the packet will be dropped which leads to the out of bound problem [3].
(c) Local maximum problem (LMP): Georouting protocols follow greedy forwarding strategy and when this strategy becomes inefficacious to relay information packets due to prevailing correspondence gaps, LMP appears [19]. LMP is a state; where a

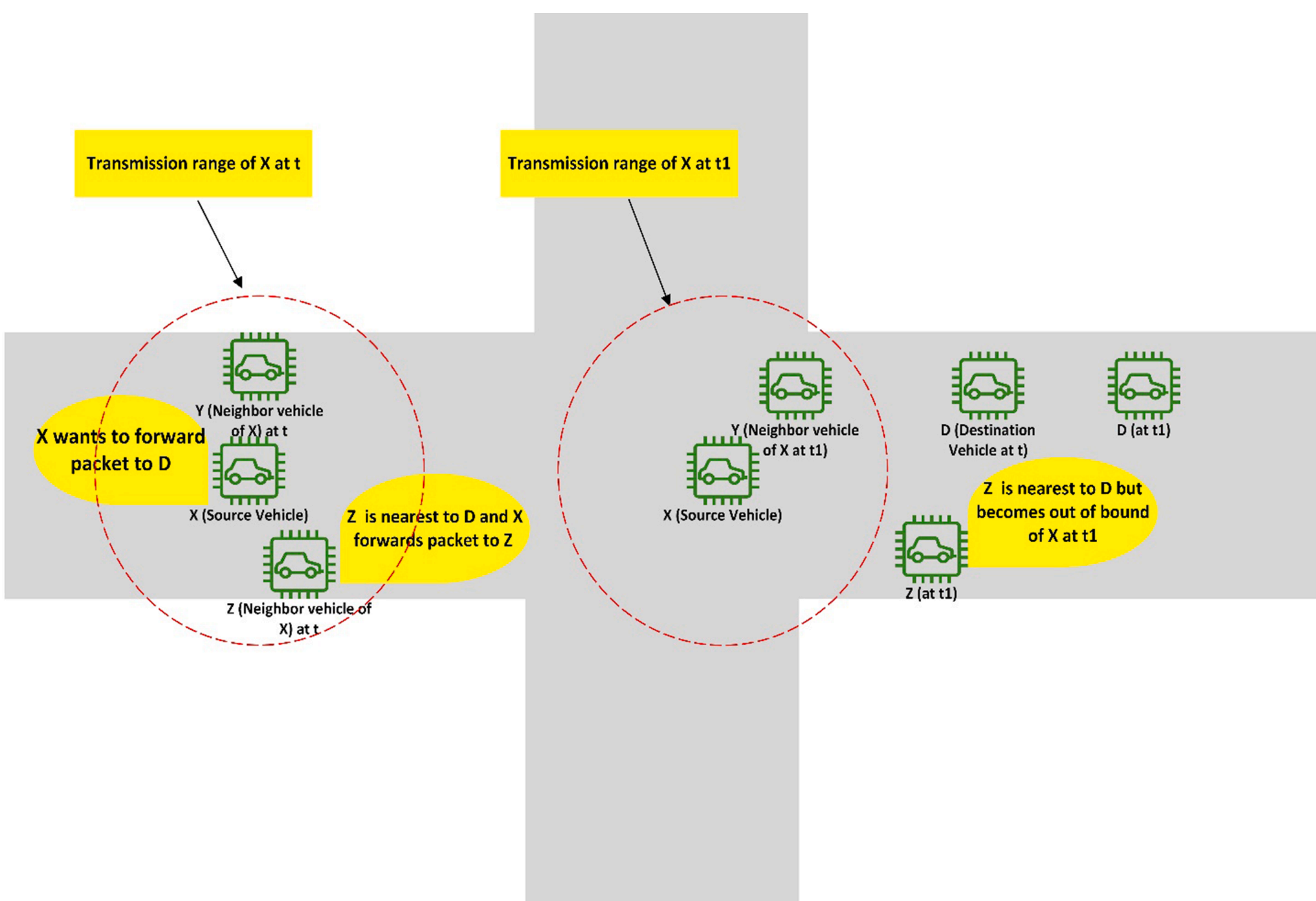


Fig. 1. Out of bound problem.

vehicle is unable to locate any neighbor nearer to destination than itself to forward an information packet. Fig. 2 illustrates LMP in which, vehicle X is a source vehicle and has neighboring vehicles Y and Z in its transmission range.

(d) Precise positioning: The main idea of georouting protocols is to acquire precise geographic vehicle location. GPS is one of the positioning techniques which fail in downtown regions or tunnels due to obstructed signals from satellite in those regions [19]. Thus, a consequential endeavor is required to attain precision in accuracy for georouting protocol designing by considering all the variations.

A lot of research has been done on connectivity issue in geographic routing, route recovery, precise positioning and forwarding methods in VANETs. Based on the type of problem, routing protocols in literature are categorized as follows.

2.1. Based on local maximum problem and route recovery

GPSR (Greedy Perimeter Routing Protocol) [14] is one of the first well known georouting protocols. It operates in two modes. In greedy forwarding mode the packets are advanced in the network based on the data belonging to instant neighbor of the router. GPSR wields the location of routers along with packet's target. Instead of relying on the data from maps, GPSR conveys the location of vehicle based on an algorithm. The greedy forwarding is valid for both planarized and non-planarized graphs. In case greedy forwarding fails due to LMP, then GPSR wields repair mode i.e., perimeter forwarding and this mode is applicable only on planarized graphs. As topology of the network alters frequently due to high mobility, therefore GPSR wields local topology intelligence to promptly locate alternative paths. GPSR strategy befits in highly vital ambience like vehicular correspondence on highway and is inefficient in city scenario [20]. Also, in perimeter forwarding across single road scenario, redundantly, numerous vehicles have to be crossed which enhance hop count and delay. In order to vanquish the shortcomings of GPSR, GSR (Geographic Source Routing) was proposed which wields city [15]. It was contemplated that map exists, as on-board navigation unit is generally installed in vehicles. Thus, the present forwarding vehicle utilizes this contemplation to reckon junction configuration (wielding Dijkstra approach) by which an information packet navigates. Greedy strategy is wielded for relaying information packet amid two junctions. Moreover, GSR employs RLS (Reactive Location Service) i.e., on demand accessibility of preferred vehicle location information in order to circumvent flooding. The GSR constraint is that it does not contemplate sufficient vehicle connectivity on the chosen road. In [21], author proposed a GPCR (Greedy Perimeter Coordinator Routing) which also utilized road maps just like GSR, but GPCR operate in two forwarding modes i.e., restricted greedy and repair approach. The restricted greedy approach prefers choosing junction vehicles amid all the neighbors in transmission range of present forwarding vehicle. Coordinator vehicle anonym is wielded for junction vehicles when vehicle encounters LMP state, then repair approach is wielded, which is the attribute of GPCR. With this approach, a vehicular node endeavor to conjecture road topology exploiting via congregation of vicinal vehicles. If forwarding vehicle is a coordinator and the packet is in repair approach, then the vehicle wields Right Hand Rule (RHR) in order to advance the packet on right path. All time presence of coordinator vehicle at junctions is the constraint of GPCR, because this is not the case in real scenarios. The probability of packet jamming in the routing loop also ameliorates due to unavailability of junction vehicle [10]. In [16] author proposed a VCLCR (VANET Cross Link Corrected Routing) routing strategy to overcome the constraints of GPCR, which inevitably

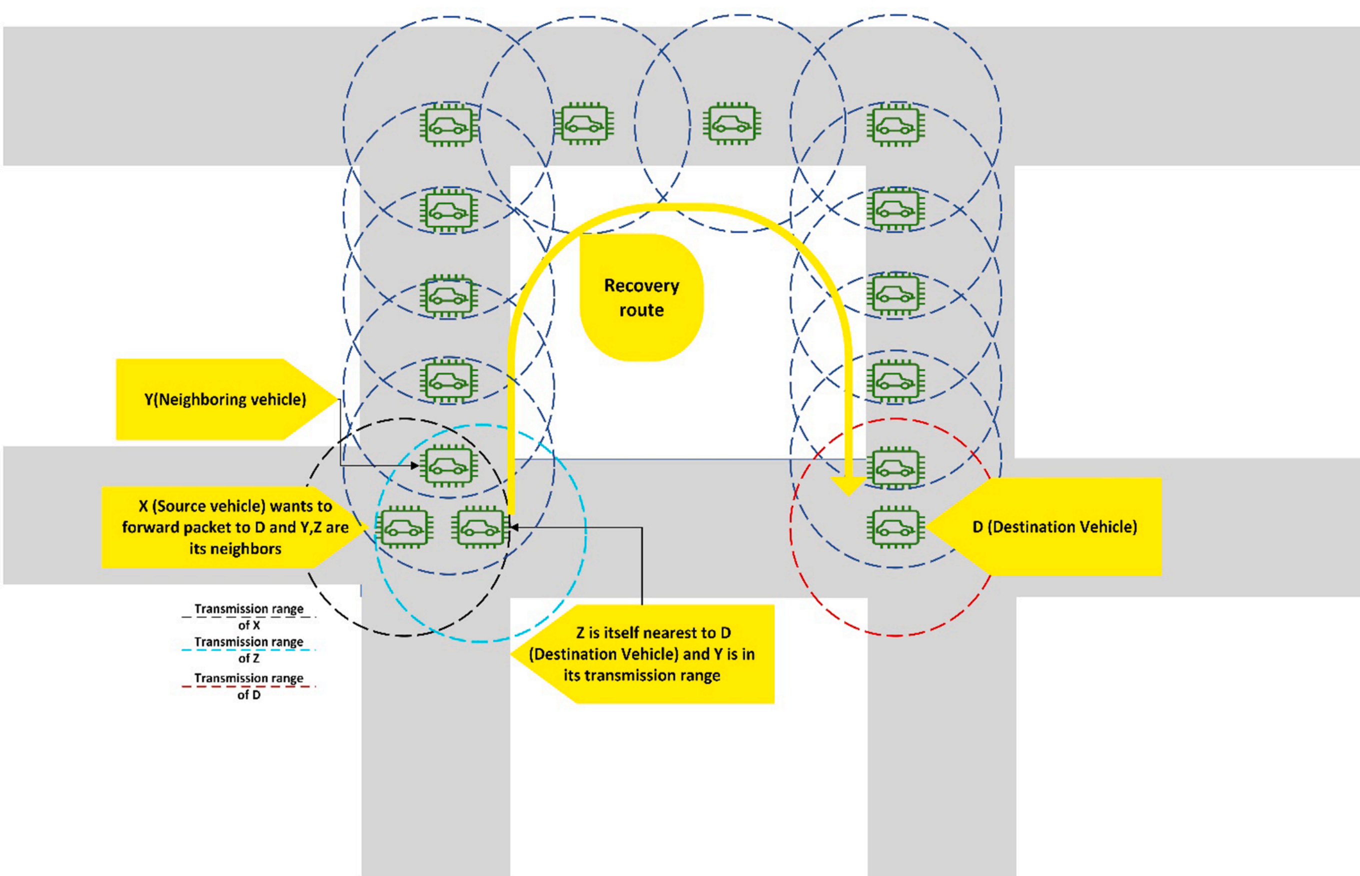


Fig. 2. Local maximum problem.

contemplates junction/ coordinator vehicle existence. By perceiving routing loop intelligence and effacing the probable cross links, VCLCR rectify the constraints of GPCR. If coordinator vehicle prevails, then the greedy forwarding approach of VCLCR advances information to that coordinator vehicle else, information is disseminated to the prevailing vehicle distant neighbor. In perimeter mode, VCLCR performs like GPCR, moreover it follows auxiliary procedure to circumvent routing loop issue. In [28] the author proposed Geographic Stateless Routing - GeoSVR. It is a stateless VANET unicast routing scheme which is coalesced with digital map and position of vehicle. Typically, it is an association of 2 quintessence algorithms i.e., restricted advancing and optimal advancing algorithm. The restricted advancing upgrades the repercussions of inconsistent wireless channel whereas optimal advancing augments the advancing strategy by operating on LMP and sparse network issue. The propounded routing is assessed in an artificial environment and simulation results stated that low latency and high packet delivery ratio was achieved by GeoSVR. Most of the georouting protocols in VANET consider static vehicle velocity amid the time frame of sending and receiving hello packet [16,20,21,28] but this is not the case in real world environment. Moreover, state-of-the-art routing protocols do not consider vehicle overtaking scenarios in which vehicle velocity changes that leads to increasing end-to-end delay and overhead. Also, due to high speed and dynamic environment of VANET the connectivity is short lived which increases route cost and decreases packet delivery ratio.

2.2. Based on forwarder selection and location prediction

The authors in (Fogue, 2015) propounded a proactive based CNPV (Cooperative Neighbor Position and Verification) approach. A cooperative strategy is wielded by CNPV which capacitates every vehicle to corroborate neighboring vehicle location by the received beacon packets. The efficacy of CNPV is then contrasted with two coherent but insecure algorithms UV-CAST and eMDR. The cooperation of network consumer is notion of this approach which can eventually deteriorate VANET reliability. In [24], a Kalman filter-based strategy was propounded for residual lifetime anticipation of a communication link. Also, to anticipate mobility patterns of vehicle, a variable-order Markov model was wielded in [29]. The study in (Yu, 2016) also employed Kalman filter to anticipate accurate vehicle location which enabled both fundamental as well as technical examination of vehicle information and simulation results presents great location anticipation. Whereas, the location history of vehicles was wielded for location anticipation in [17] based on equation of motion. In [7], author proposed a novel Kalman filter-based approach for Cognitive Radio Vehicular Ad hoc Networks (CR-VANETs). In order to vanquish high latency and spectrum scarcity issue in VANETs, the proposed approach chooses best vehicle by coalescing Kalman prediction and cognitive intelligence to create a substantial route amid source and destination. The authors in [6] propounded a Kalman filter-based approach for location anticipation and the results were then contrasted with ANN (Artificial Neural Network) and results demonstrate that Kalman filter performed better than ANN. Similarly, extended Kalman filter (EKF) was employed in [9] for location anticipation of vehicles and results were than compared with Kalman filter-based anticipation, which suggests that EKF provided better location anticipation. An SPEA (Strength Pareto Evolutionary Algorithm) was proposed to find the optimal path for disseminating information among vehicles in a VANET environment [8]. The authors [30] proposed a TDMP routing protocol that predicts the vehicle position based on speed and acceleration information exchange among vehicles and provides QoS parameter enhancement for the VANET environment.The authors [31] proposed an Extended Kalman Filter Greedy Perimeter Stateless Routing protocol (EKF-GPSR), to predict vehicle mobility but did not address the LMP issue and contrasted the results with the GPSR protocol. A W-GeoR (Weighted Geographic) routing protocol was also proposed which provided a faster next-hop selection of nodes for the urban VANET environment [25].

As per the literature survey, research to reconcile constraints of georouting protocols using Kalman and extended Kalman filter is limited. Based on the aforesaid issues and facts, we propose hybrid EK-PGRP based on extended Kalman filter protocol to diminish overhead and location error while increasing neighbor location prediction rate in Internet of Vehicles (IoV). Fig. 3 illustrates various phases followed in modeling of the proposed protocol i.e., EK-PGRP. The terms anticipate/ predict are used interchangeably throughout this paper.To the best of our knowledge, no effort has been made to resolve routing issues for IoV network, all the research has been carried out on VANETs only.

Categorically, this paper provides following contributions: (1) Implements PGRP protocol and integrate and adapts the Extended Kalman filter in PGRP algorithm to predict location of neighbor precisely and resolves OBP issue in V2V communication; (2) Resolves LMP issue by Perimeter Predictive Algorithm; (3) Demonstrates the effect of mobility and node density on neighbor location prediction through simulations; (4) Quantitative comparison and performance estimation with existing state of the art protocols in highway and urban IoV (Internet of Vehicles) environment.

3. System model and assumptions

Internet of Vehicles (IoV) is proposed as a global network of wireless access technology accredited vehicles comprising Internet and involving five kinds of heterogeneous network architecture. One of the IoV network architecture is V2V communication via WAVE (IEEE 802.11p) technology [11]. IoV is a combination of 3 elements, i.e., cloud, connection and client applications as shown in Fig. 4. ‘Cloud’ signifies the IoV brain and it offers various services like processing of big data and intelligent computing. Then, ‘connection’ maintains communication amid cloud and vehicles in order to access smart services of cloud-based servers. The connection taken here for the modeling is V2V (vehicle to vehicle) communication. The ‘client applications’ of vehicles use smart cloud-based services via connection. Client applications of V2V communication are further classified into safety, navigation, diagnostics and remote telematics applications. In order to predict neighbor vehicle location, it is exigent to create a system model that contemplates attributes of IoV (Internet of Vehicles) [22].

An IoV having V_n vehicular nodes is assumed, such that V_n: $\{1,2, \ldots, |V_n|\}$. Every vehicle in the network is enabled with GPS (Global Positioning System) device that provides real time velocity and location of the vehicle and steering angle of vehicle remains unchanged as vehicle travel through highway or in the city. A uniform distribution is followed by vehicle velocity from $[0, V_{max}]$ and V_{max} is maximum vehicle velocity limit. Any vehicle k state at time stamp t is represented by sextuple as $S_k(t)$: $[l_x, v_x, a_x, l_y, v_y, a_y]$, where l_x and l_y are latitude and longitude directions and v_x, v_y, a_x and a_y are constituents of velocity and acceleration across latitude and longitude, respectively. A communication link is setup amid two vehicles if they are neighbors and distance between them is smaller than T_R (transmission range). System model used in designing the vehicular environment is shown in Fig. 4. SUMO (Simulation for Urban MObility) simulator is used to model the real-world behavior of vehicular traffic. For wireless communication, every vehicle has an On-Board Unit (OBU) and it is presumed that at every time, each vehicle transmit information which is the case in client applications like safety and navigation. To compute vehicle state, equation of motion as given in Eq. (1) is wielded, where l_{t-1}, v_{t-1} and a_{t-1} are location, velocity and acceleration of vehicle at time stamp t-1 and dt signify time interval in velocity variation.

$$l_t = l_{t-1} + v_{t-1} \times dt + \frac{1}{2} a_{t-1} dt^2 \quad (1)$$

Then, the vehicle state S can be represented by following Eq. (2).

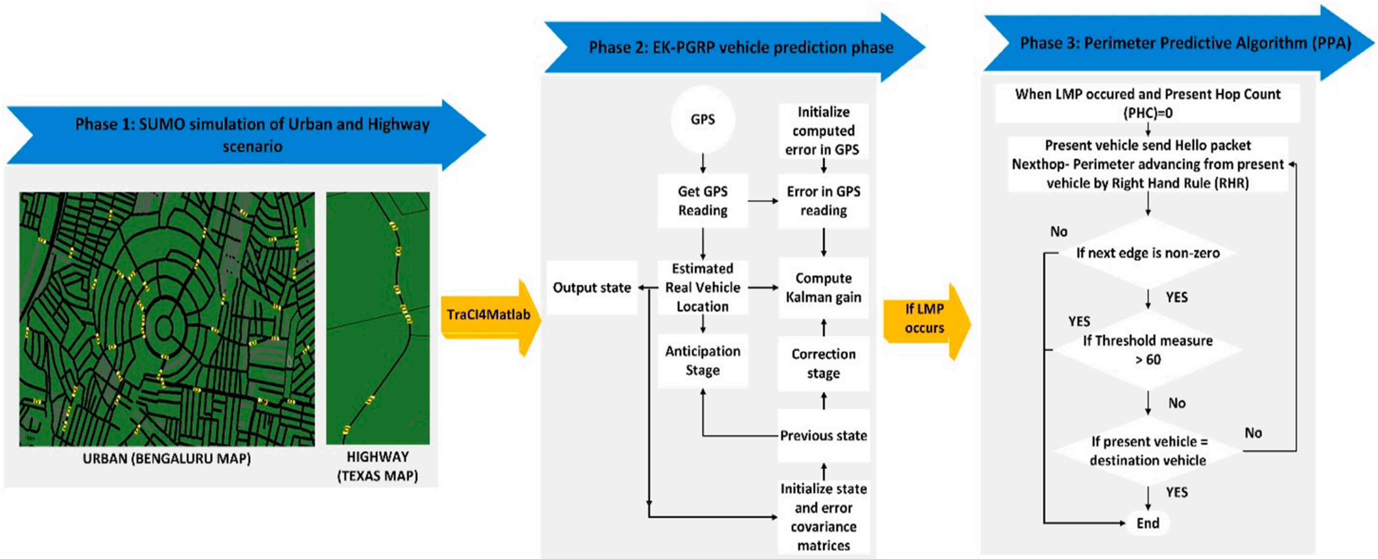


Fig. 3. Various phases involved in the modeling of EK-PGRP protocol.

$$S=\begin{bmatrix} l_x \\ l_y \\ v_x \\ v_y \\ a_x \\ a_y \end{bmatrix}=\begin{bmatrix} l_{x(t-1)}+v_x\times dt \\ l_{y(t-1)}+v_y\times dt \\ v_{x(t-1)}+\ a_x\times dt \\ v_{y(t-1)}+\ a_y\times dt \\ a_{x(t-1)}+\dfrac{dv_x}{dt} \\ a_{y(t-1)}+\dfrac{dv_y}{dt} \end{bmatrix} \tag{2}$$

Where, $l_{x(t-1)}$, $l_{y(t-1)}$, $v_{x(t-1)}$, $v_{y(t-1)}$, $a_{x(t-1)}$ and $a_{y(t-1)}$ are components of calculated vehicle state at time stamp (t-1). Also, $\frac{dv_x}{dt}$ and $\frac{dv_y}{dt}$ are change in acceleration of vehicle in latitude and longitude, respectively.

3.1. Problem formulation

Let us assume two vehicles k and l $\in V_n$. At t_1, l is the neighbor of k and at t_2, l disappears from T_R of k. Therefore, to predict location of neighbor accurately and to reduce communication overhead, the EK-PGRP protocol isproposed in this paper. Suppose, $V_n(k)$ is the set of real neighbors of k at time t and $V_n'(k)$ is the set of neighbors observed by k, then the statement of problem is stated as follows:

1st Description: In order to predict the location of neighbors in IoV, the neighbor prediction accuracy (NPA) is to be maximized and neighbor fallacious observation (NFO) is to be minimized by Eqs. (3) and (4), respectively.

$$NPA=max\sum_{k=1}^{V_n}\frac{|V_n(k)\cap V'_n(k)|}{V_n(k)}\Big/V_n \tag{3}$$

$$NFO=min\sum_{k=1}^{V_n}\frac{|V_n(k)/V'_n(k)|+|V'_n(k)/V_n(k)|}{|V_n(k)|}\Big/V_n \tag{4}$$

Where, $V_n(k)$: set of real neighbors of vehicle k, $V'_n(k)$: set of neighbors observed by vehicle k.$|V_n(k)/V'_n(k)|$ represents non observed neighbors of vehicle k and $|V'_n(k)/V_n(k)|$ represents fallacious observed neighbors of vehicle k.

4. Extended Kalman filter overview

The extended Kalman filter (EKF) is wielded for non-linear state equation [2], whereas Kalman filter [12] is designed for linear system. In EKF, the covariance matrix and updated state remain linear functions, whereas state transition matrix in Kalman filter is replaced via jacobian of state equation. Real life system dynamics and observation model are rarely globally linear. Therefore, to linearize function, taylor jacobians and expansions are wielded. Process and measurement equation for non-linear system are given by Eqs. (5) and (6) respectively.

$$S_t=f(S_{t-1},\ U_{t-1},N_{t-1}) \tag{5}$$

$$Y_t=h(S_t,\ Z_t) \tag{6}$$

Where, S_t: present state vector, $S_{t|t-1}$: Priori state vector which is estimated by S_{t-1}(previous state vector), U_{t-1}: control vector at time stamp t-1, N_{t-1} : system error noise at time stamp t-1 and Z_t: measurement noise on GPS at time stamp t.

4.1. EKF prediction

EKF is also a two-step process i.e., prediction and then correlation. Eqs. (7) and (8) represents the location prediction and error covariance computation.

$$S_{t|t-1}=f(S_{t-1},U_{t-1},N_{t-1}) \tag{7}$$

$$E_{t|t-1}=A_tE_{t-1}A_t^T+B_tQ_tB_t^T \tag{8}$$

Where, $E_{t|t-1}$: Covariance matrix of the priori error, E_t: covariance error at time stamp t, Q: Process noise covariance at time stamp t.

4.2. EKF correction

The correction (D) and Kalman gain (K_t) for EKF is given by Eqs. (9) and (10) respectively.

$$D=Y_t-h(S_t,Z_t) \tag{9}$$

$$K_t=E_{t|t-1}F_t^T\left(F_tE_{t|t-1}F_t^T+G_tR_tG_t^T\right)^{-1} \tag{10}$$

After calculating K_t, the updated state estimate ($S_{t|t}$) and error covariance ($E_{t|t}$) are evaluated by Eqs. (11) and (12) respectively.

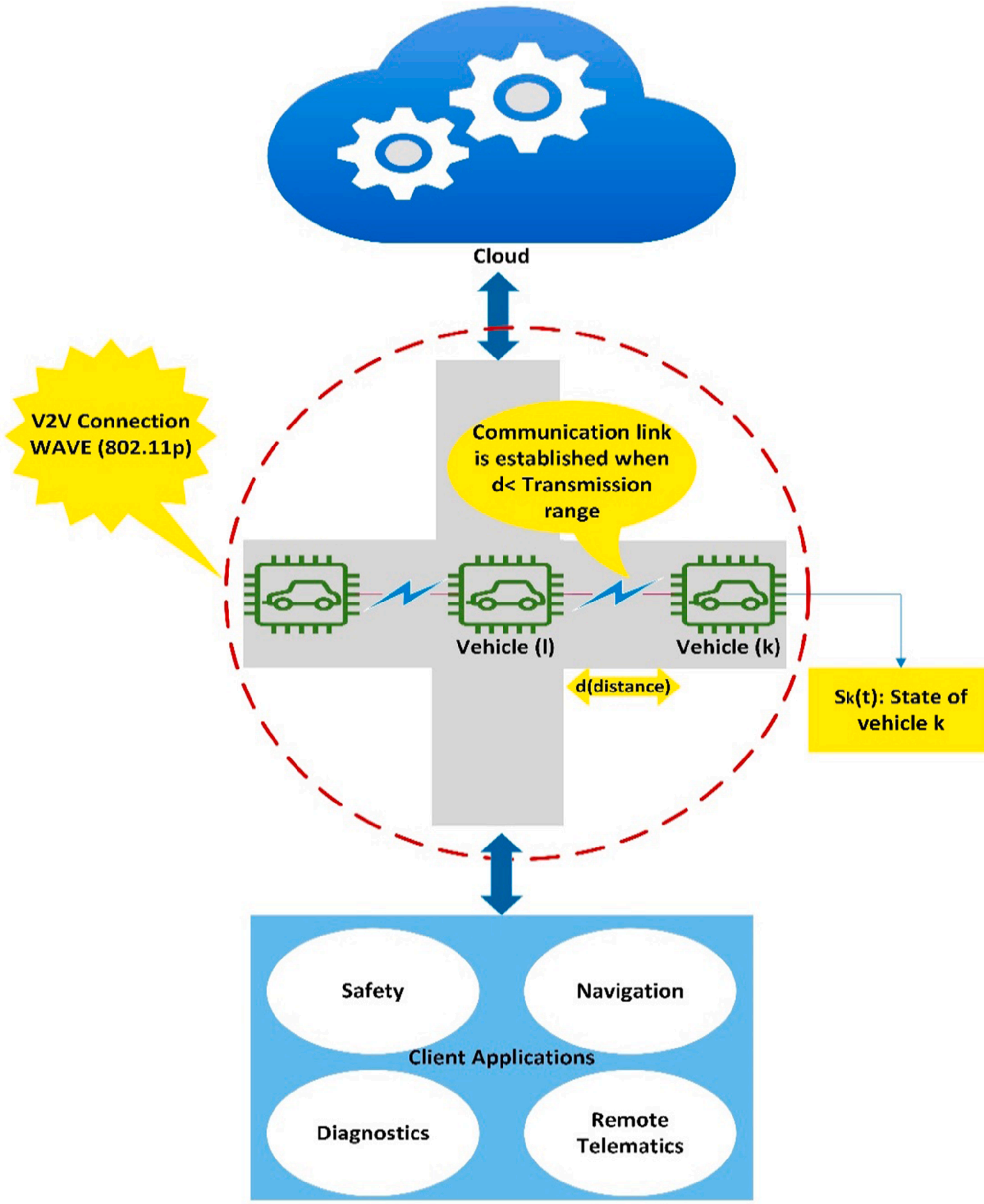


Fig. 4. System model.

$$S_{t|t} = S_{t|t-1} + K_t D \tag{11}$$

$$E_{t|t} = (1 - K_t H_t) E_{t|t-1} \tag{12}$$

The new symbols introduced in Eqs. (8) and (10) of EKF are $A_t, B_t, F_t and G_t$ and rest of the symbols used in EKF are same as that of KF symbols. Moreover, $A_t^T,\ B_t^T,\ F_t^T\ and\ G_t^T$ are transposed versions of $A_t, B_t, F_t and G_t$, respectively, which represents jacobian matrices as illustrated in Eqs. (13)–(16).

$$A_t = \frac{\delta f(S_{t-1}, 0, 0)}{\delta S} \tag{13}$$

$$B_t = \frac{\delta f(S_{t-1}, 0, 0)}{\delta N} \tag{14}$$

$$F_t = \frac{\delta h(S_t, Z_t)}{\delta S} \tag{15}$$

$$G_t = \frac{\delta h(S_t, Z_t)}{\delta Z} \tag{16}$$

The jacobian matrix A_t is evaluated through partial differentiation of $f(S_{t-1}, U_{t-1}, N_{t-1})$w.r.t S_{t-1}. Likewise, $B_t, F_t and G_t$jacobian matrices are obtained by partial differentiation of $f(S_{t-1}, U_{t-1}, N_{t-1})$w.r.t N_{t-1} and $h(S_t, Z_t)$ w.r.t S_t and Z_t. Here, U_{t-1} and N_{t-1} are supposed to be zero. Therefore, Eq. (5) becomes $f(S_{t-1}, 0, 0)$and the measurement model $h(S_t, Z_t)$remains unaltered.

5. EK-PGRP routing protocol

The paper presents a hybrid EK-PGRP routing protocol, which wields extended Kalman filter as a prediction module in PGRP [13] routing protocol in order to anticipate the neighbor location and to select the propitious neighbor for advancing packets from source to destination vehicle in both highway and urban environment. Also, if LMP state is encountered, it uses predictive prediction algorithm of PGRP algorithm to overcome that state. In order to anticipate neighbor vehicle location, the present node (i.e., vehicle) in PGRP assign weight to neighboring vehicles based on direction and distance parameters only and velocity parameter is not considered which can degrade the connectivity of two vehicles in high mobility environment leading to high packet loss and degrading throughput. Moreover, PGRP wields local information by discerning one-hop neighbors. Therefore, every vehicle advances the packet which is accurate from local point of view, i.e., follows greedy approach and this conventional greedy concept is applied on the future predicted positions. Thus, at every instant, PGRP fails to provide a global optimum solution as it discerns one- hop neighbors based on local information only. As, extended Kalman filter is well known for its prediction accuracy. Therefore, it is employed in PGRP and results suggest that it provides remarkable improvement in QoS parameters and predict neighbor vehicle location more accurately. EK-PGRP follows three step process i.e., vehicle mobility anticipation, neighbor localization and perimeter predictive state, which are described in Fig. 5 and explained in subsequent sections. Also, angle between neighbor and destination is evaluated for more precise results. When a vehicle enters the network, its state is represented by Eq. (2). By wielding Eqs. (5) and (6), present vehicle (k) anticipates $S_{t|t-1}$ for itself and neighboring vehicles. Vehicle k then checks the location prediction error after obtaining its real time location. If location prediction error is not in pertinent range, then a hello packet is broadcasted by vehicle k having vehicle_id, real time location, acceleration, velocity, and time stamp. Due to high mobility of vehicle in real world V2V environment, the out of bound issue takes place i.e., the previously received neighbor's information may have altered before receiving the next beacon packet. Thus, out of bound issue is resolved by wielding one-step advanced prediction as in Eqs. (7) and (8). Subsequently, vehicle k utilizes Eqs. (9)–(12) for EK-PGRP in order to update second step of its anticipation model to obtain $S_{t|t}$. Else, vehicle k will not broadcast any Hello packet and keep on wielding the same anticipation model variables. After receiving the hello packet from vehicle (k), vehicle (l) will append its velocity, location and acceleration information to the packet. As vehicle l has the same anticipation model like vehicle k, so vehicle l will carry out the EKF correction step for vehicle k and always yield the latest updates.

In EK-PGRP correction step, every vehicle in the network records their own S_t, where $t = 0, 1, \ldots,$. Let the S_t for every vehicle do not vary significantly within dt. Then, the vehicle state S_t can be represented by Eq. (2). Initially, 6×6 matrix S_t is represented by Eq. (17).

$$S_t = \begin{bmatrix} 1 & 0 & dt & 0 & dt^2/2 & 0 \\ 0 & 1 & 0 & dt & 0 & dt^2/2 \\ 0 & 0 & 1 & 0 & dt & 0 \\ 0 & 0 & 0 & 1 & 0 & dt \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{17}$$

Term dt represents time interval and for simplicity, dt = 1. Every vehicle in the network also updates their error covariance ($E_{t|t-1}$) as per present velocity, acceleration and location. As vehicle enter into the network, its actual location is described by 2×1 vector carrying l_x and l_y just like S_t. But the state of vehicle S_t is a 6×1 vector. Therefore, Y_t matrix extricates the vehicle location information from S_t. Thus, Y_t is represented by Eq. (18).

$$Y_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{18}$$

No prior measurements are considered for the onset of estimation problem. Considering the realistic V2V scenario, initially, $S_0 = Y_0$i.e., first state is equal to first measurement. And the diagonal elements of error covariance matrix are preferred to have large values and off diagonal elements are set to zero [7]. Thus, initial value of error covariance matrix E_0 is given in Eq. (19).

$$E_0 = 10,000 \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} = 10,000 \times (U_{6\times6}) \tag{19}$$

Were, U: unit matrix. As per the system model requirement, Q and R values i.e., process and measurement noise are determined. Generally, an ad-hoc approach is wielded to determine their values [7]. Thus, initial values of Q and R are described in Eqs. (20) and (21).

$$Q = 0.001 \times (U_{6\times6}) \tag{20}$$

$$R = U_{2\times2} \tag{21}$$

The value of U_{t-1} and N_{t-1} are supposed to be zero in Eq. (5). Therefore, the initial values of Jacobian matrices $A_t, B_t, F_t and G_t$ are given in Eqs. (22) and (23). The value of A_t is obtained by partial differentiation of $f(S_{t-1}, 0, 0)$w.r.t S_{t-1} and for B_t, the partial differentiation of $f(S_{t-1}, 0, 0)$ is performed w.r.t N_{t-1}.

$$A_t = \begin{bmatrix} 1 & 0 & dt & 0 & 0 & 0 \\ 0 & 1 & 0 & dt & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{22}$$

$$B_t = 0_{6\times6} \tag{23}$$

Where,0: zero matrix of 6×6 order. $F_t and G_t$ jacobians are evaluated by performing partial differentiation on $h(S_t, Z_t)$ w.r.t S_t and Z_t, respectively, and their initial values are described by Eq. (24).

$$F_t = G_t = U_{6\times6} \tag{24}$$

Where, U: Unit matrix of 6×6 order. Algorithm 1 illustrates the pseudo code of vehicle mobility anticipation.

In order to detect the departure of old neighbor at each time slot, vehicle k evaluates distance amid neighbors and itself, which is defined as anticipated distance (A_D). If A_D is greater than T_R (transmission range); vehicle k will disconnect the link with corresponding neighbor. This process will diminish the bandwidth consumption required for neighbor discovery significantly. Algorithm 2 illustrated the pseudo code for neighboring vehicle localization.

5.1. Perimeter predictive algorithm (PPA) for LMP route recovery

In order to transmit information in LMP (Local Maximum Problem) situation, a vehicle cannot detect any other neighboring vehicle nearest to the destination vehicle than itself and it is explained in Fig. 2. When LMP occurs, then K-PGRP/ EK-PGRP follow PPA (Perimeter Predictive Algorithm).

In PPA, a network is disconnected if next hop equal to perimeter advancing from present vehicle with RHR (Right Hand Rule) and second edge is zero. If next edge is non-zero, then to check connectivity threshold measure (T_M) is evaluated. PHC, MHC and LHC in PPA refer to present hop count, maximum hop count and least hop count required for network connectivity. MHC was set to 12 and LHC was set to 2 for simulations. The packet must meet these limits otherwise packet is dropped. After performing simulations for 1500 times, it was observed that if LHC > PHC, then network remains connected and if PHC > LHC, it ameliorates the chances of network disconnection and when PHC = MHC, the network gets disconnected. Also, if next edge is present vehicle (PV), then network gets disconnected and packet is sent back to the point where it entered PPA.

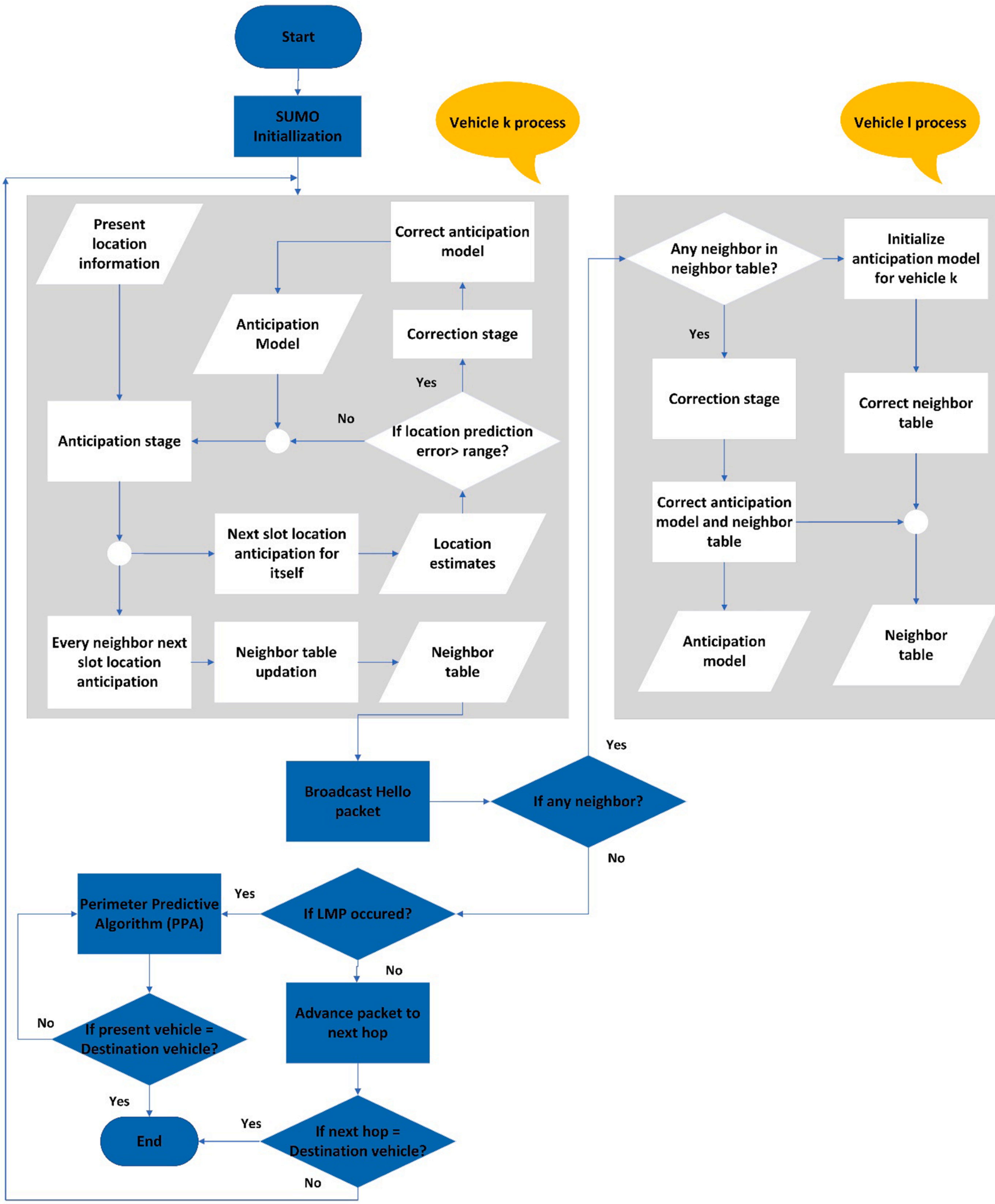


Fig. 5. Flowchart of EK-PGRP routing.

Algorithm 1
Vehicle mobility anticipation by K-PGRP/ EK-PGRP.

Data: The initial state S_t of vehicle. The vehicle set Ψ. The initial value of U_{t-1} and N_{t-1} are zero. The initial neighbor table (incorporating itself). Initial values of $M_t, H_t, R, Q, E_0, A_t, B_t, F_t and G_t$.
Result: Vehicle location anticipation
Result: Vehicle location anticipation
for any vehicle k ∈ Ψ
for any vehicle I ∈ k′s neighbor table
do
A: Use Eqs. (7) and (15) to anticipate one step ahead state for EK-PGRP, respectively;
B: Use Eqs. (8) and (16) to anticipate error covariance for K-PGRP and EK-PGRP, respectively;
C: Use Eqs. (10) and (18) to calculate K_t for K-PGRP and EK-PGRP, respectively;
D: Use Eqs. (11), (12) and (19), (20) to calculate $S_{t|t}$ and $E_{t|t}$ for K-PGRP and EK-PGRP, respectively;
end for
end for

Algorithm 2
Neighbor localization.

Data: The updated state estimate ($S_{t|t}$) of vehicles. The initial neighbor table (incorporating itself).
for any vehicle k ∈ Ψ
for any vehicle l
if l is neighboring vehicle of k
Anticipate distance amid k and l by utilizing the anticipated state data;
end if
if $A_D > T_R$
Broadcast hello packet and update neighboring vehicle table;
end if
end for
end for

$$T_M = max\left(\frac{PHC - LHC}{MHC - LHC}\right) \tag{25}$$

T_M is evaluated by Eq. (25). If $T_M > 60\%$ then network gets disconnected. Algorithm 3 elaborates Perimeter Predictive Approach.

6. Simulation settings and performance evaluation

In this section, the performance evaluation of proposed EK-PGRP routing protocol is contrasted with K-PGRP and state-of-the-art PGRP and GPSR routing protocols in urban and highway scenario. Rician and Rayleigh fading are considered for highway and urban scenario, respectively. Two-ray ground model was wielded at physical layer to specify physical propagation. IEEE 802.11p standard is wielded at MAC layer. MATLAB R2018a and SUMO simulator were used for performance estimation of routing protocols. TraCI4Matlab [1] was wielded in order to enable client-server mechanism amid Matlab (client) and SUMO (server). SUMO was wielded to create both real world urban scenario of Bengaluru city, India and Texas State Highway130 scenario. Bengaluru is considered for simulation because according to report of location technology company TomTom [27], for 2020 year, Bengaluru takes the title of highly congested city in the world. Also, Texas State Highway 130 is considered for highway scenario generation. Both the scenarios meet prerequisites for proposed routing protocols. Simulation settings for EK-PGRP are described in Table 1.

Algorithm 3
Perimeter predictive algorithm.

If source vehicle is best in contrast with all its nighboring vehicle
Choose a neighboring vehicle wielding Right Hand Rule
end if
if next edge is present vehicle
Compute T_M
else network is disconnected
if $T_M < 60\%$
Advance to the next hop
else network is disconnected
if present vehicle is destination vehicle
Network is disconnected
else choose a neighboring vehicle wielding Right Hand Rule
end if
end if
end if

7. Performance metrics

The accurate neighbor location prediction is prerequisite for an efficient routing protocol. The efficiency of EK-PGRP is measured in terms of NPA (Neighbor Prediction Accuracy), NFP (Neighbor Fallacious Observation), AHC (Average Hop Count), PDR (Packet Delivery Ratio) and CR (Cost of Routing) in both urban and highway scenario by varying vehicle speed and vehicle density. The results are then contrasted with PGRP and GPSR geographic routing protocols.

7.1. NPA (neighbor prediction accuracy) and NFO (neighbor fallacious observation)

NPA metric shows the percentage of real neighbors which are observed by vehicle k to its each neighbor incorporating the real observed and non-observed neighbors. NPA is given by Eq. (3). NFO metric analyze the percentage of vehicles that are real neighbors but not observed/ so far not the neighbor, yet observed as a neighbor. NFO is given by Eq. (4).

7.2. Packet delivery ratio (PDR)

It is described as the total successful packets delivered to the destination vehicle by total packets transmitted from source vehicle. PDR evaluates that how accurately any routing protocol attunes to varying topology of network which in turn leans on streamlined discovery of neighbor.

7.3. Cost of routing (CR)

For every routing protocol, cost of route is evaluated by Eq. (26):

$$CR = \frac{P + RCP}{T} \tag{26}$$

Where, P: number of hello packets, RCP: routing control packets which incorporates route request, route error and route response packets and T: data throughput. The neighbor discovery mainly expedites the routing process by assisting routing protocol thereby reducing the cost of routing.

Table 1
General framework specifications.

Parameter	Specification
Number of vehicles	20,40,60,80,100,120,140,160,180,200
Transmission range	400 m
Simulation area	Highway (10,000) m
	Urban (3500 × 3500) m
Propagation Model	Two-ray ground
Maximum vehicle speed	18 km/h–108 km/h
Packet Length	512 bytes
Fading Model	Rician (Highway) and Rayleigh (Urban)
Length of vehicle	5 m
Beacon interval	1 s
Simulation time	500 s
Vehicle acceleration	2.4 m/s^2
Type of antenna	Omni-directional
Vehicle deceleration	4.5 m/s^2
PHY-MAC protocol	IEEE 802.11p

8. Results and discussion

In order to estimate the precision of neighboring vehicle table, NPA metric performs key role. The routing protocol performance is directly affected by the accuracy of neighboring vehicle table. The NPA metrics contrast for EK-PGRP, K-PGRP [23], PGRP and GPSR routing protocol in urban and highway environment for varying vehicular speed and vehicular density is illustrated in Figs. 6 and 7, respectively. From Fig. 6 (a) and (b), it is clear that the proposed protocol i.e. (EK-PGRP) and its variant K-PGR Pameliorates the average NPA rate by 2.91% and 4.53% w.r.t PGRP in urban environment, whereas in highway environment, the average NPA rate for EK-PGRP and K-PGRP is ameliorated by 1.88% and 4.36% w.r.t PGRP protocol. It can be discerned from Figs. 6 and 7 that the proposed protocol obtained higher NPA in contrast with PGRP for varying vehicular speed and density. Higher NPA is a result of precise prediction technique applied in the proposed protocols.

Fig. 7 depicts the effect of varying vehicular density on NPA in urban and highway environment. The proposed protocol i.e. (EK-PGRP) and its variant K-PGRP ameliorates the average NPA rate by 1.76% and 2.87% w.r.t PGRP in urban environment, whereas in highway environment, the average NPA rate for EK-PGRP and K-PGRP is ameliorated by 1.09% and 2.93% w.r.t PGRP protocol. Due to jacobian computation involved in EK-PGRP, it's NPA is less w.r.t K-PGRP protocol. Though, GPSR has highest NPA in all the scenarios due to greedy forwarding leading to minimum Predict Time Interval (PTI), therefore GPSR predicts the neighboring vehicles rapidly at the cost of recurrent hello packet broadcasting and end up with fallacious neighbors in the neighboring vehicle table leading to loss of packets in information delivery.

NFO metric plays vital role in order to validate and analyze neighbor prediction protocol efficiency. The loss of packets in information delivery amid vehicles is caused due to presence of fallacious neighbors in neighboring vehicle table. Minimum NFO value is a prerequisite in vehicular environment for saving resources and energy. The NFO metrics contrast for EK-PGRP, K-PGRP, PGRP and GPSR routing protocol in urban and highway environment for varying vehicular speed and vehicular density is illustrated in Figs. 8 and 9, respectively. From Fig. 8 (a) and (b), it is clear that the proposed protocol, i.e. (EK-PGRP) and its variant K-PGRP maintains NFO percentage even at 90 km/h speed and it is as low as 12.2% and 11.9%, respectively, w.r.t PGRPin urban environment; whereas in highway environment at a speed of 90 km/h, the NFO percentage difference for EK-PGRP and K-PGRP is 11.6% and 11.1%, respectively, w.r.t PGRP protocol. Extended Kalman filter used in EK-PGRP helps to maintain NFO parameter even when the speed varies from 18 to 108 km/h, thereby showing the efficacious neighbor discovery. GPSR has the highest NFO value which increases abruptly with vehicle speed due to greedy scheme employed in it and results in degrading the protocol performance.

The effect of vehicular density on NFO can be observed from Fig. 9. Fig. 9(a) and (b) depicts that even when vehicular density increases to 200, the NFO rate for EK-PGRP and K-PGRP is as low as 8.1% and 7.5%, respectively, w.r.t PGRP in urban environment; whereas in highway environment, the NFO percentage difference for EK-PGRP and K-PGRP is 7.6% and 7.1%, respectively, w.r.t PGRP protocol. Therefore, EK-PGRP adapts with increasing vehicular density and maintains lowest NFO rate whereas GPSR has highest NFO rate implying the presence of more fallacious neighbors in neighboring vehicle table.

Packet Delivery Ratio (PDR) is described as the total successful packets delivered to the destination vehicle by total packets transmitted from source vehicle. From Fig. 10(a) and (b), it is clear that in high-speed vehicular environment, the proposed protocol i.e. (EK-PGRP) and its variant K-PGRP ameliorates the average PDR rate by 14.17% and 7.02% w.r.t PGRP in urban environment, whereas in highway environment, the average PDR rate for EK-PGRP and K-PGRP is ameliorated by 13.37% and 6.12% w.r.t PGRP protocol. Also, results demonstrate that in highway due to sparse network connection and high mobility of vehicles, PDR obtained is less w.r.t urban scenario in all the cases.

The effect of varying vehicular density on PDR is depicted in Fig. 11. From Fig. 11(a) and (b), it is clear that the proposed protocol i.e. (EK-PGRP) and its variant K-PGRP ameliorates the average PDR rate by 23.04% and 17.62% w.r.t PGRP in urban environment, whereas in highway environment, the average PDR rate for EK-PGRP and K-PGRP is ameliorated by 20.24% and 14.40% w.r.t PGRP protocol. Thus, EK-PGRP illustrates remarkable improvement in PDR over K-PGRP, PGRP and GPSR protocol which showcase the efficiency of EK-PGRP to attune in varying network topology which in turn leans on streamlined discovery of neighboring vehicle.

Cost of Routing (CR)metrics depicts the performance of the proposed EK-PGRP protocol. Fig. 12 depicts the effect of vehicle speed on cost of routing for four routing protocols. It is observed that EK-PGRP require least CR to deliver data amid vehicles due to its capability of precise mobility prediction. PGRP and GPSR perform less satisfactorily in contrast with EK-PGRP. Moreover, CR increase with vehicle speed for all the four protocols but EK-PGRP maintains CR value even for 108 km/h speed. The value of CR is less for highway environment because there are a greater number of lanes on highway which leads to more throughput thereby decreasing cost of routing in comparison to urban environment.

The effect of varying vehicular density on CR is depicted in Fig. 13. As density of vehicles increases, number of hops increases which leads to a greater number of hello packets and congestion in the network thereby increasing the CR for every routing protocol. However, EK-PGRP maintains least CR due to efficient neighbor discovery technique

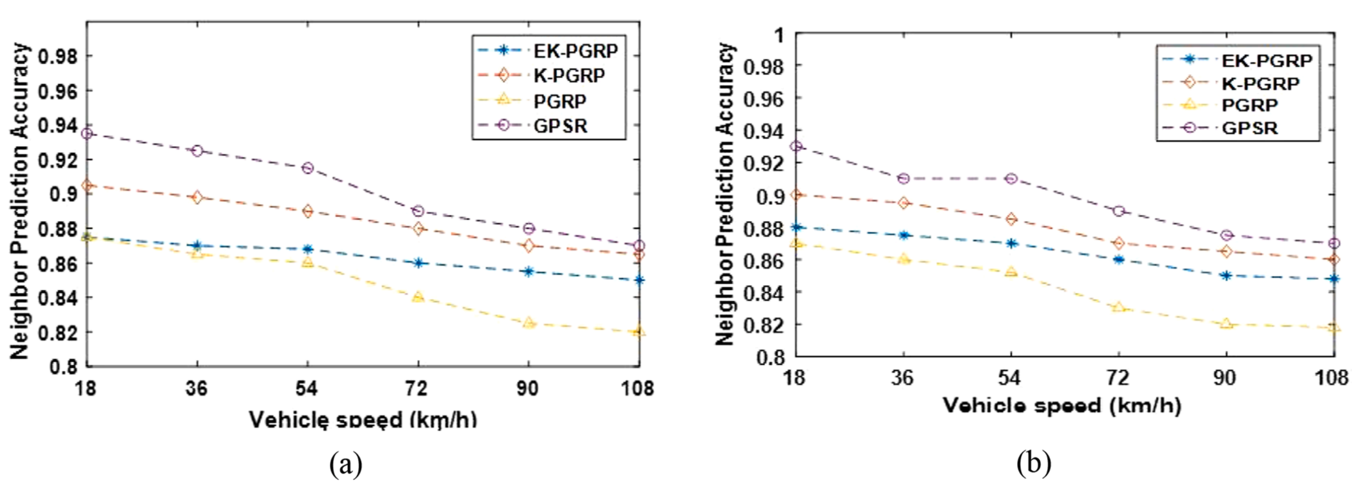
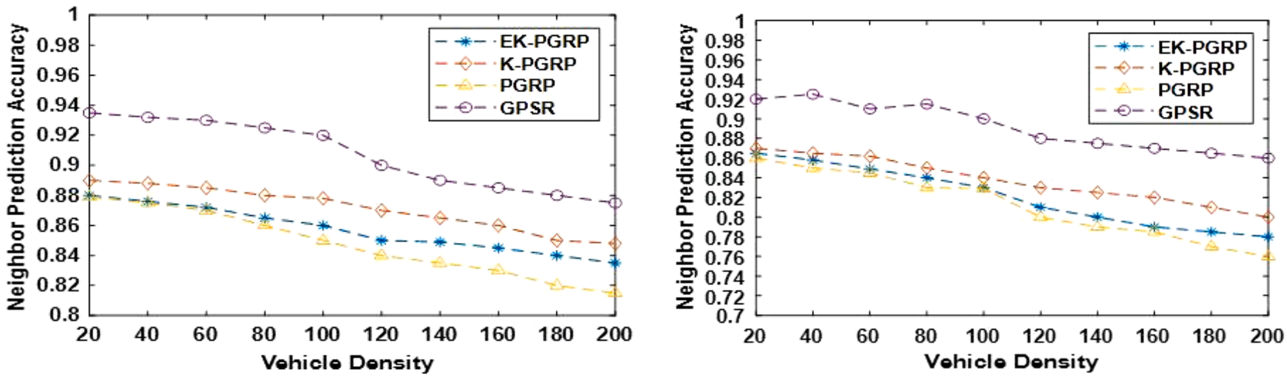
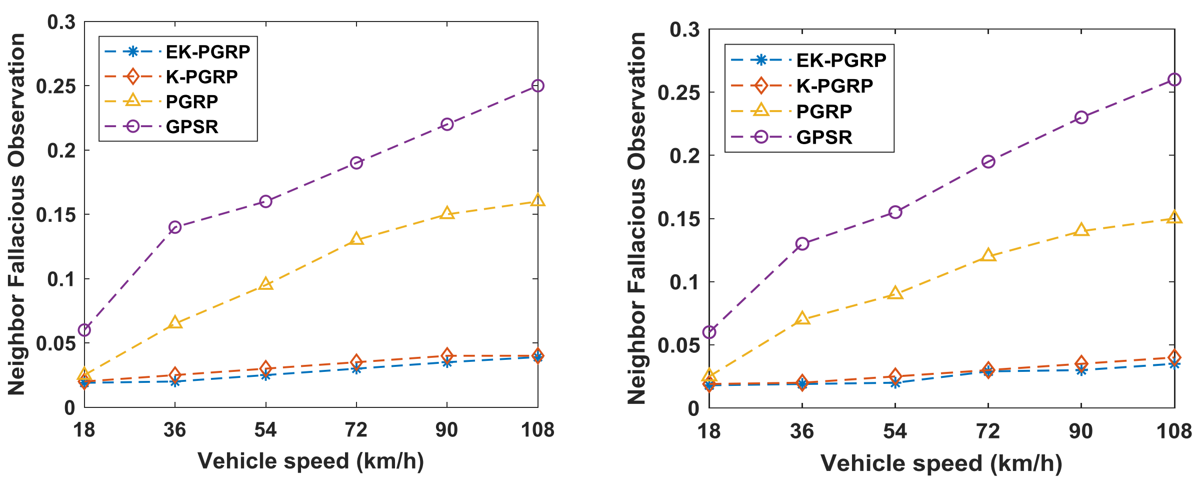


Fig. 6. The effect of vehicle speed on NPA. 6(a) Variation of NPA in urban environment 6(b) Variation of NPA in highway environment.



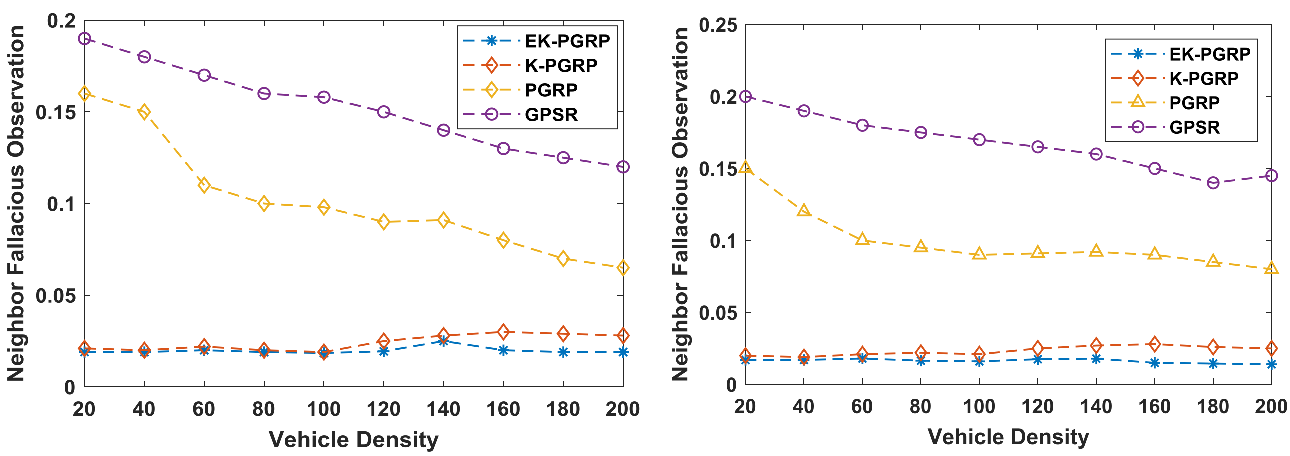
(a) (b)

Fig. 7. The effect of vehicle density on NPA. 7(a) Variation of NPA in urban environment 7(b) Variation of NPA in highway environment.



(a) (b)

Fig. 8. The effect of vehicle speed on NFO. 8(a) Variation of NFO in urban environment 8(b) Variation of NFO in highway environment.



(a) (b)

Fig. 9. The effect of vehicle density on NFO. 9(a) Variation of NFO in urban environment 9(b) Variation of NFO in highway environment.

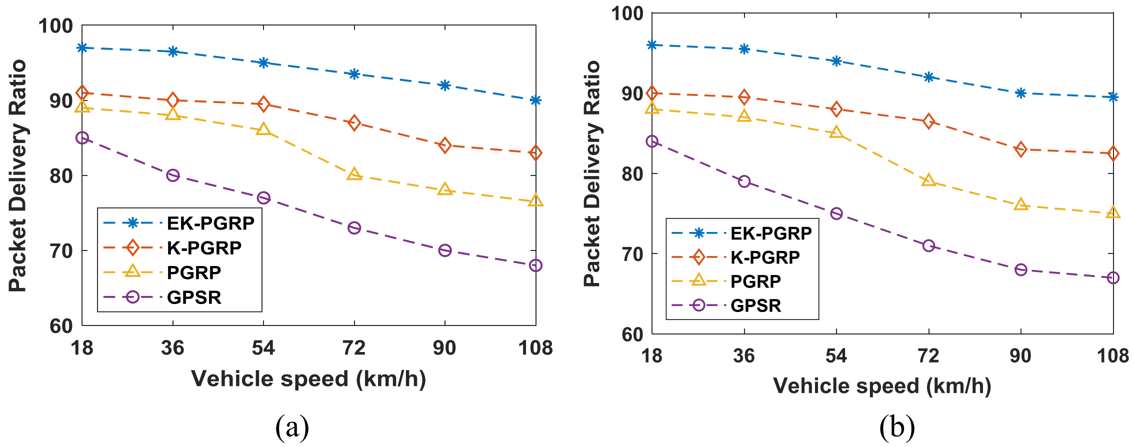


Fig. 10. The effect of vehicle speed on PDR. 10(a) Variation of PDR in urban environment 10(b) Variation of PDR in highway environment.

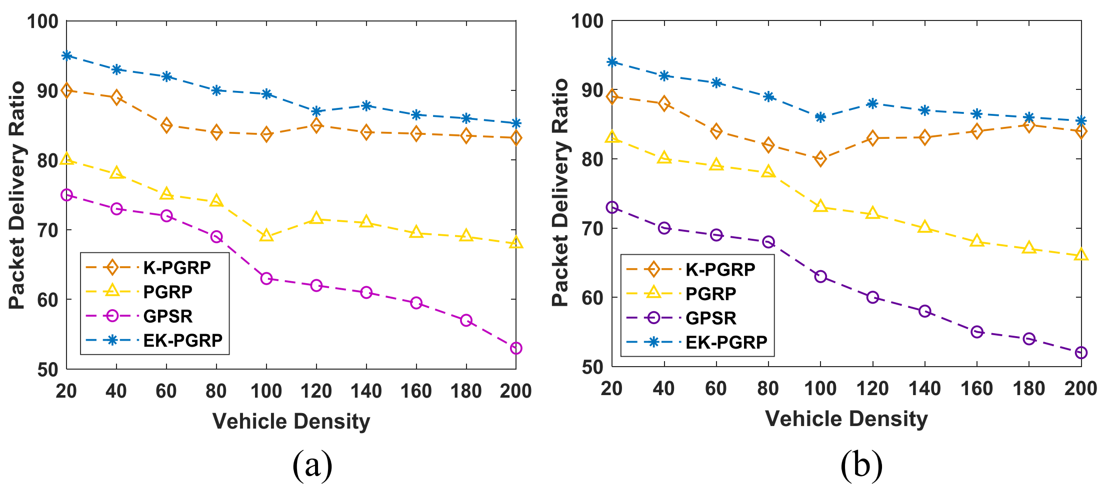


Fig. 11. The effect of vehicle density on PDR. (a) Variation of PDR in urban environment (b) Variation of PDR in highway environment.

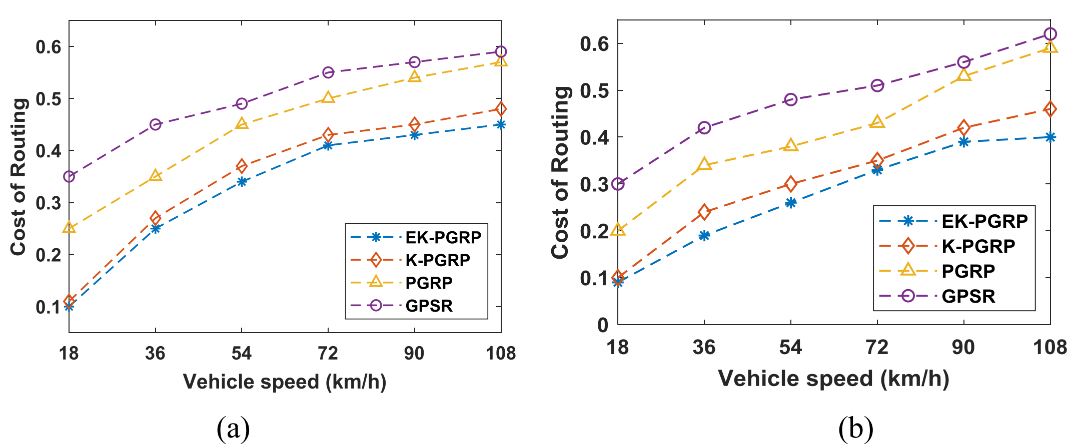


Fig. 12. The effect of vehicle speed on CR. (a) Variation of CR in urban environment (b) Variation of CR in highway environment.

employed in it and requires less hello packets thereby maintaining better CR value in contrast with all the three protocols.

9. Conclusion

The high-speed and dynamic topology variation in a vehicular environment leads to fallacious neighbor discovery and wrong packet forwarding in the network. Such an environment makes routing a very challenging task. Thus, the paper presents a novel EK-PGRP routing protocol based on extended Kalman filter to predict neighboring vehicle position for real-time V2V communication in both urban and highway vehicular environment and to efficiently transmit data from source to destination vehicle by reducing routing overhead.According to spatial and temporal movement attributes, every vehicle in EK-PGRP has an

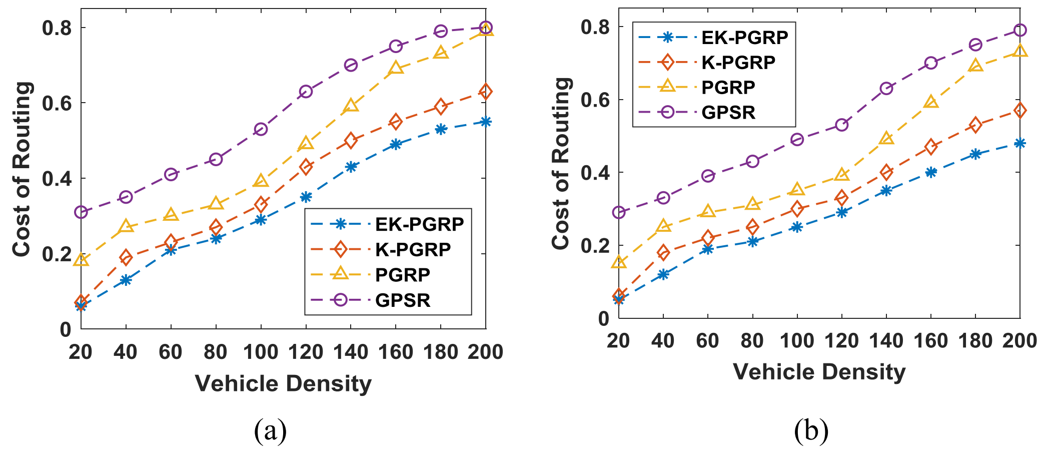


Fig. 13. The effect of vehicle density on CR. (a) Variation of CR in urban environment (b) Variation of CR in highway environment.

anticipation model to anticipate its own and neighboring vehicle mobility. MATLAB R2018a is used to simulate and analyze the results of EK-PGRP with state-of-the-art routing protocols. Simulation results suggests that EK-PGRP predict vehicle position precisely with least routing overhead among all the four routing protocols. Also, EK-PGRP has least neighbor fallacious observation rate with increasing speed and vehicular density in contrast with other routing protocols in both urban and highway IoV environment. EK-PGRP also outperforms state-of-the-art routing protocols in terms of packet delivery and routing cost and can be applied in road traffic safety applications as it ensures real time data communication amid moving vehicles. In future, we plan to implement ANN based learning to the proposed prediction protocol in order to enhance the accuracy of the prediction protocol in both highway and urban vehicular environment.

Authors contributions

All authors are approved for this work.

Author statement

Not applicable.

Data availability statement

Not applicable.

Funding

No fund received for this project.

Ethical approval and human participation

No ethics approval is required.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Code availability

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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