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Integrated cooperative localization for Vehicular networks with partial GPS access in Urban Canyons

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ABSTRACT

Accurate and ubiquitous localization is the driving force for location-based services in Vehicular Ad-hoc NETworks (VANETs). Most of present vehicle localization systems rely on Global Positioning Sytems (GPS). In urban canyons, GPS suffer from prolonged outages. Other vehicle motion sensors (e.g. gyroscopes, accelerometers and odometers) suffer from unsustainable error accumulation. This research presents a novel Cooperative Localization scheme that utilizes Round Trip Time (RTT) for inter-vehicle distance calculation, integrated with Reduced Inertial Sensor System (RISS) measurements to update the position of not only the vehicle to be localized, but its neighbors as well. We adopted the Extended Kalman Filter (EKF), to limit the effect of errors in both the sensors and the neighbors' positions, in computing the new location. Our scheme is also extended to account for the scenarios where some of the vehicles might experience GPS availability for a short duration. The ultimate aim of this work is to efficiently manage and coordinate this heterogeneous set of sensors/technologies into a consistent, accurate, and robust navigation system. Different scenarios using different velocities and neighbors' densities were implemented. GPS updates with different percentages and error variances were also introduced to test the robustness of the proposed scheme. The scheme is implemented and tested using the standard compliant network simulator 3 (ns-3), vehicle traces were generated using Simulation of Urban MObility (SUMO) and error models were introduced to the sensors, the initial and the updated positions. Results show that our RISS-based scheme outperforms the non-cooperative RISS typically used in challenging GPS environments. GPS updates with low error variance can enhance the accuracy of the proposed cooperative scheme and share this enhancement among the network. Moreover, we compare our proposed scheme to a GPS cooperative scheme and demonstrate the reliability of a RISS-based cooperative scheme for relatively long time duration.

1. Introduction

Location-Based Services (LBS) and applications in vehicular environments are experiencing rapid development in areas such as automatic parking, safety monitoring, traffic and resource management [1,2]. Moreover, they have been extended to cooperative forms such as collision warning, cooperative driving and adaptive cruise control [1,3,4]. Since a high degree of positioning accuracy, in sub-meters, is a mandate of these applications, utilizing the Dedicated Short Range Communication (DSRC) is very promising. DSRC is a spectrum of 75 MHz allocated by the U.S. Federal Communications Commission in the 5.9 GHz band. As such, DSRC [5] enables vehicle-to-vehicle and vehicle-to-infrastructure communication in Vehicular Ad-hoc NETworks (VANETs). This communication is furthermore governed by the physical and Medium Access Control (MAC) protocols defined in the Wireless Access in Vehicular Environments (WAVE) in IEEE 802.11p, resulting in efficient spectrum utilization.

Such developments in LBS and applications necessitate pervasive precise localization of vehicles. Global Navigation Satellite Systems (GNSS) such as Global Positioning System (GPS) provide location information with accuracy of 5–10 m. However, this level is not guaranteed in urban canyons [6] where the satellite signals typically experience excessive multipath due to high rise buildings. Moreover, this signal requires open sky access, which is unavailable in tunnels. As a solution, a plethora of advanced positioning techniques was introduced in the literature to handle these out-

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ages. The most widely presented is integrating GNSS with other navigation systems such as Radio-Frequency IDentification (RFID) [7], Wireless Local Area Network (WLAN) [8] or Inertial Navigation Systems (INS), among others. INS uses measurements from the on-board inertial sensors to apply Dead Reckoning (DR) technique that updates the current position of a vehicle based on the last known position, the current speed and displacement (obtained from the accelerometers), and the heading measurements (obtained from the gyroscopes) [9]. However, in GPS-free environments such as tunnels and urban canyons, the above conventional integration techniques are sub-optimal because of the extra cost required for deploying reliable infrastructures such as RFID and WLANs. While inertial sensors suffer from inherent errors like bias drifts and scale factor instabilities which accumulate over time due to the double integration of the acceleration to obtain the displacement in case of protracted GPS outages. Accordingly, cooperative localization is thoroughly addressed and anticipated to achieve the required accuracy in VANETs [6].

Vehicular cooperative localization exploits the DSRC capability and allows vehicles to update their positions using both: positions of their surrounding neighboring vehicles and, the measured inter-vehicle distance through ranging techniques. In particular, some neighboring vehicles can obtain position updates only during partial access to GPS or in the existence of nearby landmarks with known positions. These vehicles can broadcast their current accurate positions and act as mobile anchors to the other surrounding vehicles with unknown or low accurate locations (denoted as vehicles to be localized). Afterwards, a ranging technique can be used to estimate the distance between the vehicles to be localized and their surrounding neighbors (potential anchors). The typical ranging techniques [5] that are widely used are Received Signal Strength (RSS), Time of Arrival (ToA), Time Difference of Arrival (TDoA) and Round Trip Time (RTT). RTT is then considered to be the best compromise among the different ranging techniques in terms of accuracy and complexity [10].

To summarize, the accuracy of the first cooperative information (i.e. neighbors' positions) depends on the localization technique used to obtain the neighbor's position. In addition, the second cooperative information (i.e. inter-vehicle distance) is subject to different sources of errors according to the used ranging technique. Therefore, the main challenges for a reliable and accurate cooperative localization are: 1) choosing the localization scheme and the ranging technique suitable for the environment, 2) mitigating the associated errors in both location and range, and 3) selecting the data fusion method for integrating the above-mentioned data.

The aim of this work is to introduce a VANETs distributed cooperative localization scheme to be used in urban canyons and tunnels where there is a complete GPS blockage and infrastructure-based localization is infeasible. Accordingly, only on-board vehicle sensors and inter-vehicle communication are used to update the vehicles' positions throughout their trajectory. Nevertheless, the scheme accounts for the scenarios where some vehicles can receive temporarily GPS updates that are further integrated with the on-board sensors for a final position update. The main outline of the introduced scheme is:

1. Our scheme applies RTT which does not require synchronization since the same vehicle will be calculating the difference between the time of transmission and reception. Moreover, RTT is proven to be robust to the channel and synchronization errors for measuring inter-vehicle distances [10]. The main challenges in RTT are the delays generated from the processing and the multipath effects at the vehicles and the packet collisions. Such processing time can be minimized by decreasing the localization overhead in the network and so, fast processing of data is guaranteed or can be statistically modeled and compensated in the calculations [11] resulting in high accurate range estimation [12]. Multipath and fading effects can be mitigated as well as in [13]. Packet collisions are typically attributed to the hidden terminal problem. However, the robustness of CSMA protocol adopted by IEEE 802.11p for VANETs will limit the occurrence of the hidden terminal problem [14]. Thus, the distance estimation using RTT requires a calibration phase to compensate for these delays.
2. Unlike previous schemes, ours updates the neighbors' locations through their on-board sensors/INS readings prior to using these positions in localization. To ensure the robustness of our scheme, both the INS sensors and the initial position errors are considered and modeled as normally distributed random variables. Accordingly, a linearized EKF was used to integrate the measured inter-vehicle distances along with the INS readings to estimate accurate positions for the vehicle to be localized in the presence of the above erroneous data. The performance of the proposed scheme is tested for different velocities compared to a non-cooperative scheme and neighbors' densities.
3. The proposed cooperative localization framework is further extended by integrating GPS positions received by some of the cooperating vehicles with the INS measurements. Such vehicles can have GPS position updates with acceptable error variances due to experiencing open sky access momentarily or using advanced satellite receivers. GPS based-position updates are coupled with INS-based positions through loosely coupled Kalman filter. The GPS-based positions are subjected to errors that are modeled as normally distributed random variables as well. These position updates can be used to improve the accuracy of the cooperating vehicles through cooperative localization especially those suffering from long GPS outages. Accordingly, heterogeneous localization schemes that integrate these GPS measurements with the WAVE protocol, used in cooperative localization, among the vehicular network are promising high accuracy compared to both non-cooperative schemes and non-heterogeneous cooperative schemes. The effect of having partial GPS updates for different number of vehicles on the performance of the cooperative scheme is also studied as well as GPS updates with different error variances. The position accuracy of our proposed scheme is compared to different cooperative and non-cooperative localization schemes.
4. We assess our introduced scheme using extensive evaluations using standard compliant network and legitimate traffic simulators. Simulation of Urban MObility (SUMO) is adopted to generate practical traffic scenarios that model the vehicles' movements. These traces are further imported by the network simulator 3 (ns-3) where the cooperative scheme is implemented using WAVE protocol for practical communication between moving vehicles.[1]

The paper is organized as follows: Section 2 reviews some of the work done in the literature. Section 3 provides an overview for the implemented distributed cooperative localization scheme. The detailed implementation of the system modules is introduced in Section 4. Performance evaluation is then provided in Section 5. Finally, Section 6 concludes the paper.

2. Literature review

Our main focus is on cooperative localization for urban canyons and tunnels where GPS is completely blocked or available for some of the vehicles over a short duration. This is unlike the cooperative schemes in [16–24] that rely mainly on GPS to update neighbors'

[1] Part of this scheme previously appeared in our work in [15].

positions, or enhance the GPS signals or positions with cooperative information.

The techniques from the literature described in [7,25] assume that only some of the vehicles are having GPS estimated positions (partial GPS availability). In [7], the RFID landmarks are used to enhance the localization accuracy of the vehicles equipped with GPS and to localize the non-equipped vehicles in range. Then, the equipped vehicles are used as a reference for the surrounding vehicles (equipped or non-equipped with GPS). While in [25] to enhance the location accuracy of each GPS equipped vehicle, the velocity measurement from the on-board sensors as well as the inter-vehicle distances are used to apply a multilateration technique where the surrounding GPS equipped vehicles are used as anchors. For the localization of the non-equipped vehicles, each neighboring vehicle provides a candidate position at different time epochs for the vehicle to be localized with assigned weighting value to be used in the multilateration. Thus, each vehicle can have different position estimates with different likelihood values measured independently using the surrounding vehicles. Then, the true position is the one with the highest likelihood.

Moving vehicles equipped with GPS receivers may only have accurate position estimates before they reach crowded areas with high buildings. Thus, to address this situation which usually happens in downtown canyons, INS with dead reckoning can be used. However, the main drawback is the error accumulation over time which deteriorates the positioning accuracy during long GPS outage. Reduced Inertial Sensor System (RISS) is introduced instead of INS since the former uses speedometer to obtain the displacement, thus one single integration is required. Although error accumulation becomes less significant, error accumulation still exists and high accuracy cannot be maintained for a long time [9]. To avoid the drawbacks of standalone RISS, some techniques based on cooperative localization in GPS denied environments are proposed in the literature as reviewed below.

In [26], a Cooperative Inertial Navigation (CIN) technique is introduced to enhance the accuracy of the standalone INS. In CIN, the vehicles share their sensor measurements alongside their INS-based positions with all the vehicles traveling in the opposite direction and then fuse these data with Carrier Frequency Offset (CFO) to estimate the position. CFO represents the difference between the transmitted and the received frequency of the carrier signal. The accuracy of the localization is enhanced in case of vehicles moving with high relative velocities.

In [27], an algorithm called VANET LOCation Improve (VLOCI), is introduced where every vehicle has the initial position measured using GPS and has a set of estimated positions calculated from the surrounding neighbors. The GPS estimated position is further enhanced using the positions of the neighbors and the inter-vehicle distances based on ToA or RSS. The inter-vehicle distance should be added to the neighbor's position or subtracted since all the vehicles are moving in the same lane and direction. The final position is calculated using the weighted average function by assigning each position a weighting value based on the neighbors' distances. Then in [28], the authors extended their work in VLOCI by adding a smart lane algorithm that takes into consideration a multi-laned road scenario. In particular, the algorithm avoids positions with sudden drifts from the GPS-based positions.

Moreover, the authors in [29] enhanced the work done in [27] and [28] by updating the scheme to provide good localization accuracy considering multiple lanes. To know the position estimate for each vehicle, Angle of Arrival (AoA) is measured in addition to the ranging techniques mentioned in the VLOCI algorithm to determine the location. Furthermore, as in the VLOCI technique, the final position is calculated using the weighted average function of the position estimates but this position is further fused along with the GPS position using EKF and/or Particle Filter (PF) for an updated position. AoA technique, however, is highly affected by the multipath that results in high localization error and thus expensive solutions such as antenna array must be used [6].

A centralized RSS cooperative approach for a cluster of n vehicles was introduced in [30] and [31]. Each vehicle measures its distance with the neighboring $(n-1)$ vehicles based on RSS. These neighbors also report their velocities from the on-board sensors. Then, all this information is collected by the n vehicles and used to compute their positions based on EKF estimates. Additionally, map matching is used to ensure that the localization is done within the permitted boundaries. In particular, the EKF uses the total $n \times (n-1)$ measurements within the cluster to 1) predict the states with the on-board velocities and 2) correct them using the RSS based distances. The main focus was to mitigate the error in the RSS-based distances. Nevertheless, the computational complexity cannot be easily handled for real time and safety applications.

Our proposed distributed scheme adopts RTT instead of RSS while EKF handles the errors in the sensors and the neighbors' positions. In the next section, the overview of the preliminaries of the system and of the implemented distributed cooperative scheme is introduced.

3. System overview

3.1. Preliminaries

We assume that all vehicles have initial positions obtained either from GPS or any other localization system [32]. Then, these vehicles travel in urban areas where GPS is unavailable due to excessive multipath from large buildings or complete blockage as in tunnels. At a given moment if there is partial access of open sky, some vehicles might receive GPS updates for a short period.

Vehicles are equipped with DSRC transceivers, so each vehicle to be localized can communicate with its neighboring vehicle in the communication range via IEEE 802.11p. The neighbors in range are the vehicles that receive messages from the vehicle to be localized with power greater than certain threshold (referred as receiver's sensitivity).

The vehicles are also equipped with inertial navigation sensors to monitor both the land vehicle's translational and rotational motion: speedometers/odometers that measure the horizontal speed and, the gyroscope that determines the heading of the vehicle. We define the following system entities:

- *Sender* is the vehicle to be localized that sends messages to the surrounding vehicles acquiring information for localization.
- *Neighbor* is the vehicle within the communication range of the sender vehicle that receives the messages and then replies to the sender with its navigation information.

Fig. 1 shows a scenario on a two-way, two-lane road where the sender (*the vehicle in the middle*) requests information (*solid lines*) from the surrounding neighbors which in turn will reply (*dashed lines*) with the navigation information.

3.2. Scheme overview

The proposed distributed cooperative localization scheme can be illustrated in the following main steps:

- The sender vehicle requiring localization broadcasts a Location Request Message (LRM) for collecting neighbors' navigation information in range (both location and sensor measurements) needed in the localization. Packet collisions and processing overhead are minimized in our framework by maximizing the

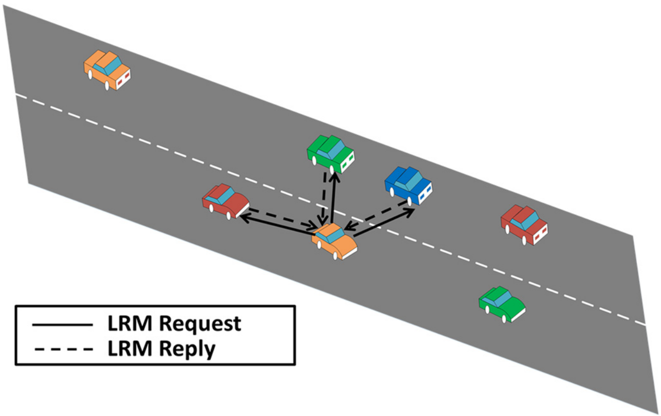

Fig. 1. Two-way, two-lane road cooperative scenario.

interval between localization request messages. Vehicles typically broadcast localization messages every t seconds while relying on inertial sensors to compute the location between intervals. Hence, our method does not exacerbate the contention between vehicles.

- The received outdated neighbors' positions are corrected at the sender by applying RISS mechanization using their reported sensor measurements. The neighbors' positions are outdated from the second-time epoch as there is no GPS updates. These outdated positions will decrease the accuracy of the position of the sender vehicle if directly used. For this reason, mechanization is done to ensure that the neighbors are having updated positions before applying the cooperative scheme.
- RTT is calculated at the sender and used to measure the actual distance d_m between the sender vehicle and the neighbor responded to the broadcasted messages.
- The sender vehicle updates its position using the RISS mechanization and the GPS measurements, if available, through loosely coupled Kalman filter. If the outdated sender position is used when calculating the Euclidean distance between it and its neighbor, this distance will be subjected to high error and will not reflect the actual distance between them.
- The Euclidean distance d_{est} is a function of both the sender's and the neighbors' positions. However, since these two positions are calculated based on RISS, they suffer from the inaccuracies of the mechanization process and the errors associated with both the sensors and the previous positions. Thus, the measured distance d_m using the ranging technique is adopted to correct the estimated distance and calculate a final accurate position of the sender vehicle.
- Linearized EKF uses the error difference between the calculated distances d_{est} and d_m to estimate the error in x and y positions of the sender vehicle. This reflects the error in d_{est} while the error in d_m is assumed to be negligible as a fact of applying RTT.
- The estimated x and y errors are then used to update the sender's position which is the output of the cooperative scheme and can be also used by other neighbors.

These steps are summarized in the block diagram in Fig. 2 which consists of the five main stages of the proposed scheme: LRM, mechanization, GPS/RISS fusion, Distances' calculation, KF and position update.

4. Cooperative localization scheme

The proposed cooperative localization scheme is illustrated in Fig. 3 and its five stages are described next.

4.1. Localization request messages (LRM)

Each sender vehicle to be localized requests neighbors' navigation information (positions, heading and speed) through broadcasting messages. The broadcast message contains both the ID of the sender vehicle denoted as sender ID and time of transmission T_{TX}.

All messages are broadcasted in the DSRC range every t seconds. The neighboring vehicle in the communication range that receives power greater than its sensitivity power level $\hat{P}$ will add its navigation information (latest positions, current heading and current odometer reading) to the message and rebroadcasts the message. The latest position of the neighbor might be outdated by the time it is reported and thus it is accompanied with the above inertial sensor readings.

Once the sender receives back the neighbor's message, it checks whether the received message is a reply to its own broadcasted LRM or not. This is done by comparing its ID with the sender ID appended in the reply message. If the IDs are identical, the message is decoded, otherwise it is ignored. The sender measures the time of reception of the LRM and denoted by T_{RX}. The LRM message contains the following information:

- Neighbor's position is denoted by coordinates $x^{(n)}$ and $y^{(n)}$ where n is the neighbor's index. This position is the last updated available one at the neighbor which might be out-

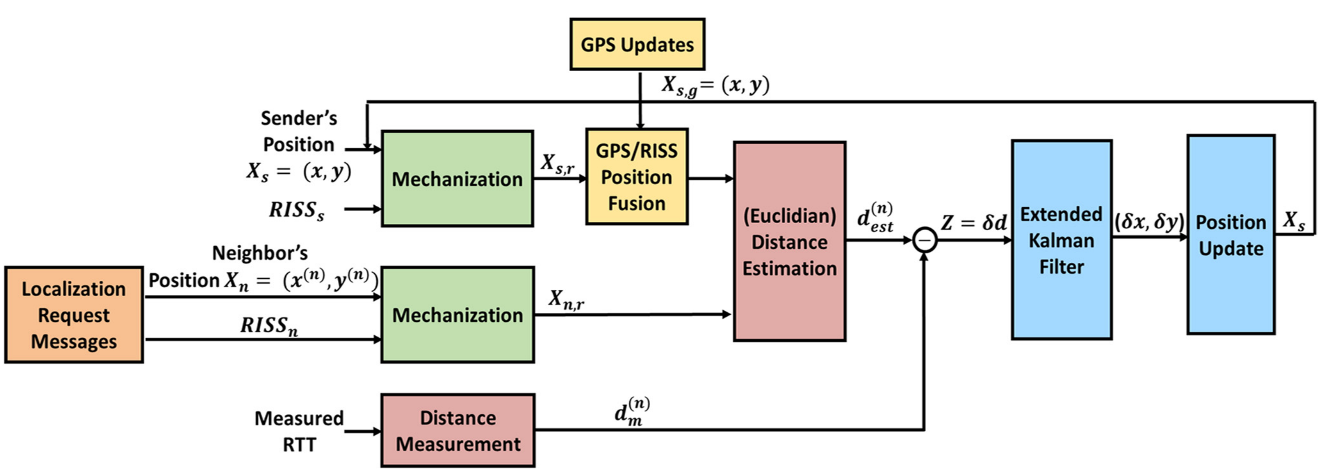

Fig. 2. Overview block diagram of the proposed cooperative scheme.

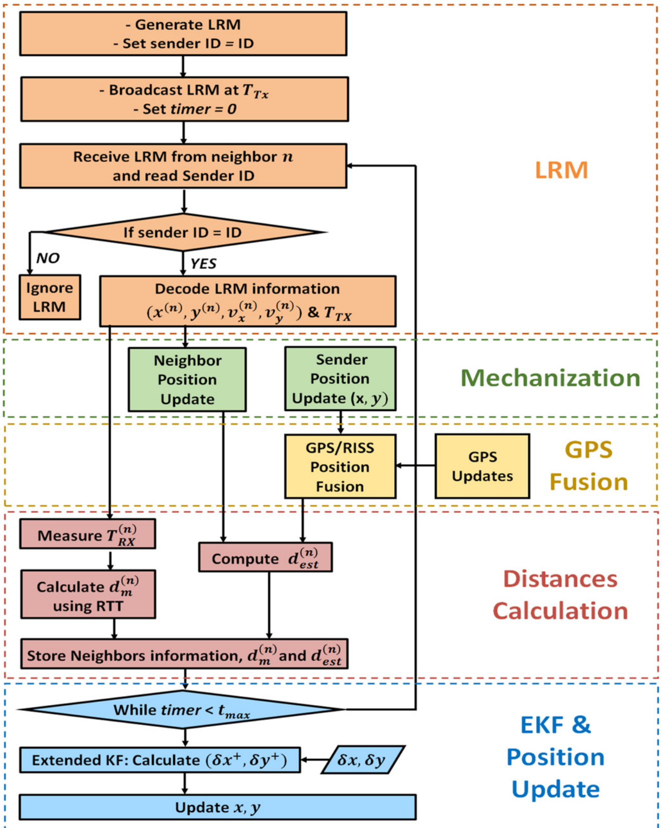

Fig. 3. Flow chart of the proposed cooperative scheme.

dated from the current time of the LRM reception. Accordingly, neighbor's velocity and heading are also broadcasted.

- Neighbor's velocities in both x and y directions, respectively, are denoted as $v_x^{(n)}$ and $v_y^{(n)}$, and obtained from the odometer readings. Similarly, the neighbor's heading is denoted as $A^{(n)}$ and measured using the gyroscope.
- Time of LRM transmission is T_{TX} and is used to measure the actual distance to the neighbor $d_m^{(n)}$ using RTT.

The above neighbor's information is used to update the received neighbor's position using RISS which will be used afterwards in the computation of the Euclidean distance $d_{est}^{(n)}$ between the sender vehicle and its neighbor n.

Both distances $d_m^{(n)}$ and $d_{est}^{(n)}$ will be described and used afterwards to update the current sender vehicle's position.

4.2. 2D RISS based neighbors and sender position update

As mentioned earlier, the neighbor reports in the LRM its last updated position which may be outdated at the time of the localization of the sender vehicle. This is because in our proposed cooperative scheme, it was assumed that all vehicles travel in urban areas where there are no GPS location updates.

We assume that our framework focuses on land vehicles in urban areas where uphill and downhill is less likely to exist. Thus, 2D RISS [9] is used to update the neighbors' positions as well as the position of the sender vehicle. This is done at lower cost compared to full inertial navigation systems (INS) as the RISS consists of only two sensors: odometer (or speedometer) and gyroscope. The information from both sensors are used to compute the velocities in the east V_E and north directions V_N. Moreover, these velocities are directly integrated to calculate the east and north displacements which in turn are used to compute the E and N positions corresponding to x and y positions, respectively. Below are the main equations used in the 2D RISS as in [33].

$$\dot{A} = w_z \tag{1}$$

$$\begin{pmatrix} V_E \\ V_N \end{pmatrix} = \begin{pmatrix} V_{od}\sin(A_t) \\ V_{od}\cos(A_t) \end{pmatrix} \tag{2}$$

$$\dot{r} = \begin{pmatrix} \dot{\phi} \\ \dot{\lambda} \end{pmatrix} = \begin{pmatrix} 0 & \frac{1}{R_M+h} \\ \frac{1}{(R_N+h)\cos\phi} & 0 \end{pmatrix} \begin{pmatrix} V_E \\ V_N \end{pmatrix} \tag{3}$$

Where:

- w_z is the angular velocity measured by the gyroscope.
- V_{od} is the vehicle's horizontal speed measured by the odometer.
- V_E and V_N are the calculated east and north velocities, respectively.
- $\dot{\phi}$ and $\dot{\lambda}$ are the rate of change in latitude and longitude, respectively.
- $\dot{A}$ is the rate of change in azimuth (heading angle).
- R_M, R_N are the meridian and the normal radius of the earth, respectively.
- h is the altitude.
- A_t is the current azimuth (heading angle) of the vehicle.

4.3. GPS updates and fusion

While each vehicle typically updates its position using the RISS, temporarily available GPS measurements can be also available. Accordingly, the output of the sender's RISS mechanization (from the previous step) is integrated with the GPS-based position using Kalman filter through a loosely coupled approach [9]. In particular, the difference between the position obtained from the RISS mechanization and that obtained from the GPS is calculated and then used to correct the sensors' measurements as well as the sender's position. The state and measurement vectors of the loosely coupled Kalman filter are denoted by $\delta X_{t|t-1}^{LC}$ and Z_t^{LC}, respectively while the state transition and design matrices are denoted by H_t^{LC} and F_{t-1}^{LC}, respectively and represented as follows:

$$\delta X_{t|t-1}^{\dot{L}C} = \begin{pmatrix} \delta\dot{\phi} \\ \delta\dot{\lambda} \\ \delta\dot{V}_E \\ \delta\dot{V}_N \\ \delta\dot{A} \\ \delta\dot{w}_z \end{pmatrix} \tag{4}$$

$$F_{t-1}^{LC} = \begin{pmatrix} 0 & 0 & 0 & \frac{1}{R_M+h} & 0 & 0 \\ 0 & 0 & \frac{1}{(R_N+h)\cos\phi} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -f_n & 0 \\ 0 & 0 & 0 & 0 & f_e & 0 \\ 0 & 0 & \frac{-\tan\phi}{R_N+h} & 0 & 0 & R_{33} \\ 0 & 0 & 0 & 0 & 0 & -\beta_{wz} \end{pmatrix} \tag{5}$$

$$G_{t-1}^{LC} = \begin{pmatrix} \sigma_\phi \\ \sigma_\lambda \\ \sigma_{V_E} \\ \sigma_{V_N} \\ \sigma_A \\ \sqrt{2\beta_{wz}\sigma_{wz}^2} \end{pmatrix} \tag{6}$$

$$Z_t^{LC} = \begin{pmatrix} \phi_r - \phi_g \\ \lambda_r - \lambda_g \\ V_{E,r} - V_{E,g} \\ V_{N,r} - V_{N,g} \end{pmatrix} \tag{7}$$

$$H_t^{LC} = (I_{4\times4} \quad 0_{4\times2}) \tag{8}$$

Where:

- $(\delta X_{t|t-1}^{LC})^+$ is the state vector.
- t is the measurement time epoch.
- $(+)$ is the superscript sign that defines the predicted value.
- F_{t-1}^{LC} is the state transition matrix that models the dynamics in the system states at each time epoch.
- f_n, f_e are the body accelerations transformed into local-level frame.
- R_{33} is the component in row 3 and column 3 of the rotation matrix.
- β_{wz} is the reciprocal of the correlation times associated with the autocorrelation sequence of δw_z.
- σ_{wz}^2 is the variance associated with the gyroscope errors.
- G_{t-1}^{LC} is the noise distribution matrix of the loosely coupled KF.
- Z_t^{LC} is the measurement/observation matrix of the loosely coupled KF between the RISS (r) and the GPS (g) measurements.
- H_t^{LC} is the design matrix that expresses the linear relation between the states and the measurements.

Finally, the output of this Kalman filter $(\delta X_{t|t-1}^{LC})^+$ will be added to the RISS measurements (X_r) as follows:

$$\left(X_t^{LC}\right) = \left(\delta X_{t|t-1}^{LC}\right)^+ + \left(X_t^r\right) \tag{9}$$

Where:

$$X_t^r = \begin{pmatrix} \phi_t \\ \lambda_t \\ V_{E_t} \\ V_{N_t} \\ A_t \\ \omega_{zt} \end{pmatrix} \tag{10}$$

After updating both the sender and the neighbors' positions, inter-vehicle distance is calculated using the ranging technique as well as the Euclidean model as described next.

4.4. Inter-vehicle distance calculation (d_{est} and d_m)

Based on the LRM collected information, localization techniques such as multilateration cannot be applied to obtain an updated position for the sender vehicle because of the associated errors in these measurements. Instead, linearized Kalman filter model such as EKF can be used to obtain an accurate position update [9].

The proposed cooperative scheme calculates two values of distances between the sender vehicle and each neighbor. The first distance denoted as $d_{est}^{(n)}$ and calculated based on the vehicles' latest positions as depicted in the equation below. It is the Euclidean distance between the RISS-based updated position of the sender vehicle and its neighbor n as computed from Subsection 4.2. Thus, this distance is subjected to errors that are associated with the vehicles' positions due to the odometer, gyroscope and the vehicles' previous positions errors.

$$d_{est}^{(n)} = \sqrt{\left(x^{(n)} - x\right)^2 + \left(y^{(n)} - y\right)^2} \tag{11}$$

Where:

- $x^{(n)}$ and $y^{(n)}$ is the RISS mechanization-based updated position of neighbor n.
- x and y is the latest position of the sender vehicle (after RISS mechanization).
- The second distance denoted as $d_m^{(n)}$ is calculated using the ranging technique RTT as shown below using the difference between the transmission and the reception time instants of the LRM at the sender and denoted as T_{TX} and T_{RX}, respectively. No error was introduced to the RTT as the delay offset that is generated from the processing can be calibrated, multipath and fading effects can be also mitigated as discussed previously. Thus, $d_m^{(n)}$ reflects the actual distance between the sender vehicle and the neighbor n.

$$RTT^{(n)} = T_{RX}^{(n)} - T_{TX} \tag{12}$$

$$d_m^{(n)} = \frac{c \times RTT^{(n)}}{2} \tag{13}$$

Where:

- $RTT^{(n)}$ is the time duration between transmitting the LRM by the sender vehicle and receiving the reply from neighbor n.
- c is the constant speed of light.

The error difference between the above two distances ($d_{est}^{(n)}$ and $d_m^{(n)}$) are used by extended Kalman filter, described below, to estimate the errors in the x and y positions of the sender vehicle.

4.5. Extended Kalman filter

As discussed earlier, the calculated distances have many sources of errors and noises associated with the measurements. To obtain accurate estimation of the current vehicle's position in the presence of such errors, Kalman Filter (KF) is used to integrate the cooperative information with the sender vehicle RISS-based location. KF is the best linear estimator when the error follows a Gaussian distribution [9] which is the case in the sensor measurements and the vehicles' positions. Typically, the system dynamics and the measurements must be represented using linearized models which is not the case in distance-based position estimation. Thus, KF works with distances and positions errors (rather than the distances and positions values) to reserve its linearity. The KF relates the error in the unknown position to the error between the two distances (i.e. RTT-based and Euclidean-based) to be compensated for final position update. In our proposed framework, we adopted Extended Kalman Filter (EKF) which utilizes a closed-loop scheme where the corrected states at the output of the filter are fed back to be used at the next time epoch in calculating the navigation states at the output of the inertial system. This is unlike KF which utilizes open-loop scheme where the corrected states are not fed back. The conventional EKF adopted in this paper consists of two stages: Prediction and measurement phases [9]. The measurement vector $Z_{t_{N\times1}}$ and the corresponding design matrix $H_{t_{N\times2}}$ are given in Eq. (14) and Eq. (15). Then, the estimated errors vector (errors in x and y positions) is used to correct the latest position of the sender vehicle according to Eq. (16) and fed back afterwards to the system to improve the future estimates of the RISS mechanization as depicted in Fig. 2.

$$Z_{t_{N\times1}} = \begin{pmatrix} d_m^{(1)} - d_{est}^{(1)} \\ \vdots \\ d_m^{(N)} - d_{est}^{(N)} \end{pmatrix} \tag{14}$$

$$H_{t_{N\times 2}} = \begin{pmatrix} \frac{(x-x^{(1)})}{d_{est}^{(1)}} & \frac{(y-y^{(1)})}{d_{est}^{(1)}} \\ \vdots & \vdots \\ \frac{(x-x^{(N)})}{d_{est}^{(N)}} & \frac{(y-y^{(N)})}{d_{est}^{(N)}} \end{pmatrix} \tag{15}$$

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} \delta x_t^+ \\ \delta y_t^+ \end{pmatrix} + \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} \tag{16}$$

Where:

- N is the total number of neighboring vehicles.
- $\binom{\delta x_t}{\delta y_t}$ is the error state vector which consists of the errors in both x and y positions.

5. Performance evaluation

5.1. Simulation settings

The vehicles' traces are generated using SUMO traffic simulator [34]. The road is divided into two lanes where the length of each lane is equal to 300 m and the width is 3 m per lane. The inter-vehicle distance is set to be around 3 m which is adequate for the urban scenario in which the vehicles are moving with low speed. The total number of vehicles is set to $N = 50$ and divided equally between lanes. During each simulation scenario, the vehicles move with constant speed suitable for urban canyon areas. The constant speed is changed in each scenario from 3 to 11 m/s.

The proposed cooperative scheme is simulated using the WAVE module in the network simulator 3 (ns-3) [35]. All the vehicles implement both UDP echo client and UDP echo server applications where the first application is used to request location messages from the neighbors while the latter responds to the messages requested by the vehicles according to our scheme flow chart in Fig. 3. Location update interval is set to 1 second (i.e. packet generation rate =1 s) for efficient spectrum utilization and avoiding network congestion. The values of covariance matrices P, Q and R in the loosely coupled KF are chosen so that the GPS positions have higher weights than the RISS. The initial parameters of the EKF are extensively tuned to minimize the Root Mean Square Error (RMSE), and reflect the variance in the measured distances and the process noise. However, the simulations will consider multiple scenarios with different error sources for extensive evaluation and thus the EKF parameters are changed as illustrated in Table 1.

5.1.1. Simulating sensor errors

The ideal measurements of the gyroscope and the odometer are imported from SUMO. For practical simulation of the mechanization process, random Gaussian errors are added to both the gyroscope and the odometer values. The odometer's error follows a Gaussian distribution with 0 mean and standard deviation equal to 10% of the speed of the vehicle as simulated in [7] and [36]. Thus, the odometer's error increases proportionally to the distance traveled by the vehicle [37].

For the simulated gyroscope, the error introduced is Angle Random Walk (ARW), which also follows Gaussian distribution with 0 mean and standard deviation equals to $2°/\sqrt{hr}$ as the practical model in [33].

5.1.2. Simulating GPS errors

In some scenarios, we assume erroneous GPS measurements either in the initial positions or the frequent position updates when the vehicles have an open sky access. Such measurements are assumed to yield a maximum position error of z meters. This is typically modeled by adding a Gaussian distributed random variable e_p with 0 mean and σ_p^2 variance whose value depends on the maximum error z and calculated as follows:

Table 1
EKF simulation parameters.

EKF parameter	Value
F_{t-1}	$\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$
G_{t-1}	$\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$
Ideal initial position: P_0^+	$\begin{pmatrix} 0.01 & 0 \\ 0 & 0.01 \end{pmatrix}$
Ideal initial position: Q_{t-1}	$\begin{pmatrix} 0.3 & 0 \\ 0 & 0.001 \end{pmatrix}$
Erroneous initial position: P_0^+	$\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$
Erroneous initial position: Q_{t-1}	$\begin{pmatrix} 0.3 & 0 \\ 0 & 0.5 \end{pmatrix}$
R_t	$I_{N\times N}$
W_{t-1}	$\begin{pmatrix} 0 \\ 0 \end{pmatrix}$

Table 2
Sensor and GPS error modeling.

Error models	Value
Odometer error	$\approx N(0, (0.1 \times \text{speed})^2)$
Gyroscope ARW error	$\approx N(0, 4)$
For $z_{GPS} = 5$ m	$\approx N(0, 1.39)$
For $z_{GPS} = 3$ m	$\approx N(0, 0.5)$
For $z_{GPS} = 2$ m	$\approx N(0, 0.22)$

Table 3
ns-3 Simulation parameters (physical layer).

ns-3 parameters	Value
Propagation loss model	Log distance
Propagation delay model	Constant speed
Minimum received power	−105 dBm
Different sensitivity levels	−105 dBm, and −75 dBm

Assume that the CDF of the GPS error should have most of the points (i.e. 99.7%) below z, accordingly

$$\mu + 3\sigma_p = z \tag{17}$$

For $\mu = 0$:

$$\sigma_p = \frac{z}{3}$$

To calculate the error variance in x and y positions:

$$\sigma_p^2 = \left(\sqrt{\sigma_x^2 + \sigma_y^2}\right) \tag{18}$$

Assume $\sigma_x = \sigma_y = \sigma_{xy}$, then

$$\sigma_p^2 = \left(\sqrt{2 \times \sigma_{xy}^2}\right)^2 = \left(\frac{z}{3}\right)^2 \tag{19}$$

$$\sigma_{xy}^2 = \left(\frac{z}{3}\right)^2 \times \frac{1}{2} \tag{20}$$

Where σ_{xy}^2 is the variance in each of x and y directions.

The different values of σ_{xy}^2 with the corresponding maximum error z and the error modeling of the sensors are shown in Table 2. All other physical layer and application parameters are summarized in Table 3.

5.2. Simulation results

To evaluate the performance and the localization accuracy of the introduced cooperative scheme, different scenarios of vehicle movements and error models are considered. The objective of this scheme is to have a good localization accuracy in urban areas compared to the typical localization techniques used. This technique is evaluated compared to the RISS technique in urban canyons with total GPS blockage assuming ideal initial position and then extended to the erroneous case. Additionally, the performance of the scheme is studied in case of having GPS updates with distinct variances and evaluated by comparing various percentage of vehicles with GPS updates. Furthermore, diverse densities of neighboring vehicles are also taken into consideration. Then our cooperative technique is compared to widely used non-cooperative and cooperative techniques.

5.2.1. Evaluation metrics

The evaluation metrics used in the simulation are the average Root Mean Square Error $\overline{RMSE_t}$ and the maximum root mean square error $\widehat{RMSE_t}$ between the true position (obtained from SUMO) and the estimated position from the localization scheme calculated as follows:

$$\overline{RMSE_t} = \frac{\sum_{i=1}^{N} \sqrt{(x_{i,t} - \hat{x}_{i,t})^2 + (y_{i,t} - \hat{y}_{i,t})^2}}{N \times S}, \quad \forall t \in T \tag{21}$$

$$\widehat{RMSE_t} = \frac{max_{\forall i \in \{1,..N\}} \sqrt{(x_{i,t} - \hat{x}_{i,t})^2 + (y_{i,t} - \hat{y}_{i,t})^2}}{S}, \quad \forall t \in T \tag{22}$$

Where:

- $x_{i,t}$, $y_{i,t}$ is the true position obtained from SUMO.
- $\hat{x}_{i,t}$, $\hat{y}_{i,t}$ is the estimated position using the localization scheme.
- S is the number of simulations.
- N is the total number of vehicles.
- i is the index of each vehicle.
- t is the time epoch.
- N is the total duration of one simulation.

In particular, for a cluster of N vehicles over a period of time T, the average RMSE at certain time instant $\overline{RMSE_t}$, in Eq. (21), is calculated by taking the average of the RMSE of all vehicles' positions as shown in the equation. This metric is used as it gives an average overview of the performance of the vehicles in different scenarios (e.g. vehicle in the middle of the road surrounded by many neighbors or vehicle at the edge with lower number of neighbors).

The maximum RMSE at a given time $\widehat{RMSE_t}$, in Eq. (22), represents the worst case scenario of a vehicle which might suffer from large sensor errors, a small number of surrounding neighbors or low accuracy in the neighbors' positions. All the simulated scenarios consider errors in inertial sensors and/or positions updates, and thus all results are averaged over $S = 50$ runs for statistical validation. We computed the confidence intervals for a 95% confidence level. The confidence intervals were found to be small for all simulations, and hence were not explicitly depicted in the figures. Our introduced Cooperative Localization (CL) scheme is evaluated in the coming sections and it is written in short as CL KF-RISS.

5.2.2. Comparison with the non-cooperative RISS

As mentioned earlier, one of the considered scenarios is that all the vehicles have initial positions obtained either from GPS or any other localization system and then, these vehicles travel in urban canyons or tunnels with total absence of GPS. Thus, to evaluate the performance of the proposed cooperative localization scheme, it is compared with respect to the 2D RISS since the latter is the typically used localization technique in urban canyons and tunnels with GPS blockage. The effect of the accuracy of the initial position on the schemes' performance is then studied.

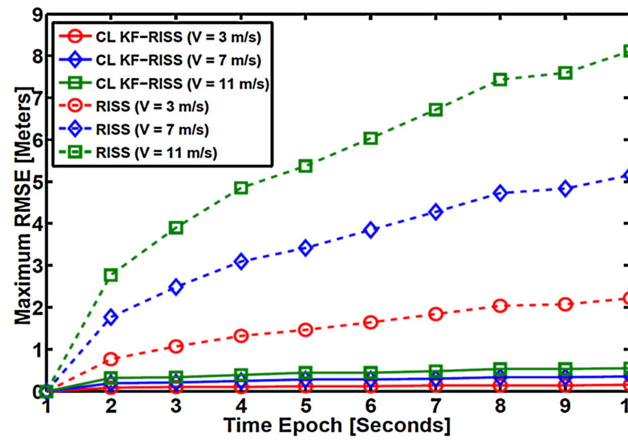

Fig. 4. Maximum RMSE comparison between the proposed scheme and 2D RISS (Ideal initial positions).

Ideal initial position In this evaluation scenario, the maximum RMSE of the proposed cooperative scheme is compared with respect to that of the 2D RISS technique for different velocities assuming perfect initial positions as shown in Fig. 4. The non-cooperative RISS suffers from rapid diversions from the true positions (RMSE increased dramatically) over time compared to the cooperative scheme. The enhancement in our proposed cooperative scheme is attributed to the frequent updates from the ranging technique RTT and the RISS-based neighbors' positions. In particular, the EKF was able to use the RTT measurements in order to correct the RISS-based predicted position's error and thus limits its accumulation over time. Therefore, for a duration of 10 seconds, the maximum RMSE of the proposed scheme has all the values smaller than 1 m compared to the RMSE of the RISS which has values up to 8 m. Such enhancement is also attained at higher velocities where the performance of RISS is highly degraded due to the increased error variance in the odometer.

Erroneous initial position Our evaluation scenario is extended by introducing an error in the initial position that follows a Gaussian distribution with variance equal to 1.39 as mentioned in Table 2. This variance is suitable for capping the GPS position error below 5 m. The EKF parameters require tuning based on the newly added source of errors (inaccurate initial positions). In particular, the initial value of the P matrix in Table 1 was increased to reflect the uncertainty in the erroneous initial position. Practically, this value can be also obtained from the standalone positioning system used in obtaining the initial position of each vehicle. Similarly, the Q matrix entry that corresponds to the error in the y position is increased to compensate the error in the initial position compared to the ideal initial position scenario discussed previously with no error in the y position since the vehicle was moving only in a straight line in the x direction. Comparing the average RMSE of the two schemes as shown in Fig. 5, the proposed cooperative scheme continues to outperform the 2D RISS over the trajectory. From the figure, the cooperative scheme was able to correct the inaccurate initial vehicles' positions using the ranging technique and the enhanced neighbors' positions. Thus, vehicles with low location error can improve the position of other vehicles with higher error using the measured distance d_m. Conversely, this enhancement is not achievable in the RISS since each vehicle continues to deviate over time from the true position as a result of error accumulation.

5.3. Effect of different neighbor' densities and sensitivity levels

In the above scenarios, the sensitivity level (i.e. minimum received power to decode the received signal) of all the vehicles was

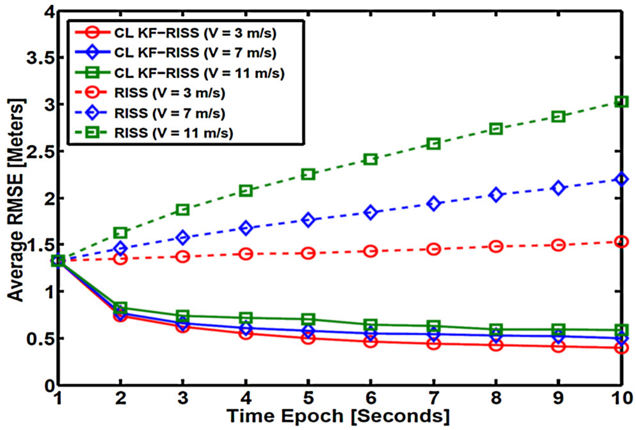

Fig. 5. Average RMSE comparison between the proposed scheme and 2D RISS (Erroneous initial positions).

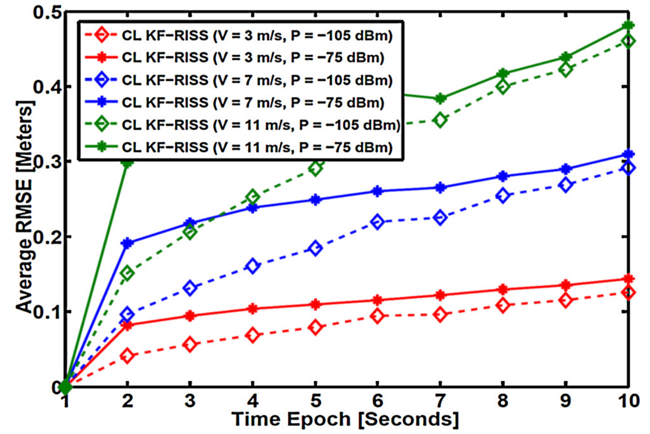

Fig. 6. Effect of the different sensitivity levels on the average RMSE of the proposed cooperative scheme.

fixed at −105 dBm. This small value resulted in large communication range that allows cooperation between all the considered vehicles. In order to evaluate the effect of the neighbors' density on the performance of our localization scheme, the above sensitivity is increased to −75. Thus, fewer neighbors will receive and respond to the LRM. Practically, these effects can be achieved by decreasing the transmitted power which is desirable for many reasons such as minimizing interference, increasing bandwidth efficiency and decreasing the energy consumption in the network. The average RMSE for the three different velocities with the presence of error in the inertial sensors assuming ideal initial positions is calculated. Fig. 6 shows the effect of the two different sensitivity levels on the localization accuracy over the time. As the sensitivity level and/or the velocity of the vehicles increases, the average RMSE becomes higher. In this figure, the power level is only increased to −75 dBm to guarantee that the minimum number of neighbors surrounding each vehicle is greater than 2 to obtain a solution by the EKF. These results demonstrate the importance of increasing the communication range in the case of fast moving vehicles in order to compensate the growing error variance of the RISS adopted in the cooperative scheme.

5.4. Effect of ideal GPS updates

Another simulated scenario is implemented where it is assumed that at certain time epochs, either all or some of the vehicles have an open sky access and thus receive GPS position updates for a short duration. To evaluate the performance of the proposed scheme, the following scenarios are considered.

5.4.1. Different percentage of vehicles with updates

At $t = 10$ and $t = 25$ seconds, it was assumed that all the vehicles can receive clear and ideal signals from the GPS satellites and thus these vehicles can have an updated position with approximately no error. After that, these vehicles would experience GPS blockage again and the cooperative scheme is used. Different percentages of vehicles with GPS updates are evaluated compared to the ideal scenario in which all the vehicles receive GPS updates to test the effect on the average RMSE as shown in Fig. 7. The percentage of vehicles with ideal GPS updates that varies between 25%, 50% and 75% of all the vehicles are implemented and compared to each other and with respect to the aforementioned ideal scenario. In addition to enhancing the RMSE of the vehicles with GPS updates, the cooperative scheme was able to broadcast these enhancements to the neighboring vehicles with GPS blockage. Such cooperation results

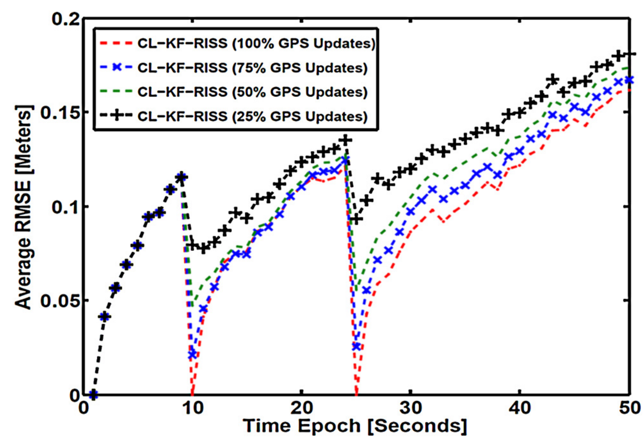

Fig. 7. Effect of different percentages of vehicles with ideal GPS updates on the average RMSE.

in enhancing the neighbors' positions where the percentage of RMSE enhancement is higher than the percentage of GPS updates.

5.4.2. GPS updates different velocities

The above mentioned cooperative gain during GPS updates is emphasized when higher velocities are considered as shown in Fig. 8. While higher velocities suffer from rapid increase in RMSE, the cooperative scheme was able to limit such deterioration with partial GPS updates to the network. Moreover, the rate of error deviation of the cooperative scheme after the GPS updates has decreased. This is due to compensating the sensors' errors by the loosely coupled Kalman filter.

5.5. Effect of erroneous GPS updates

At the selected time slots ($t = 10$ and $t = 25$), we assume that all the vehicles have erroneous GPS updates. Error variances of values of 1.39 and 0.5 are implemented to reflect a max error of 5 m and 3 m, respectively and compared to GPS updates with zero error. Fig. 9 shows the average RMSE over 50 seconds for vehicles moving with velocity equal to 3 m/s. From this figure, the erroneous GPS updates affect the performance of the cooperative scheme and make the average and the maximum RMSE worse. This is because the error introduced in the GPS position is larger compared to the errors in the motion sensors (odometer and gyroscope). In addition, the proposed scheme compensates the motion sensors' errors using cooperation. Therefore, GPS updates will only

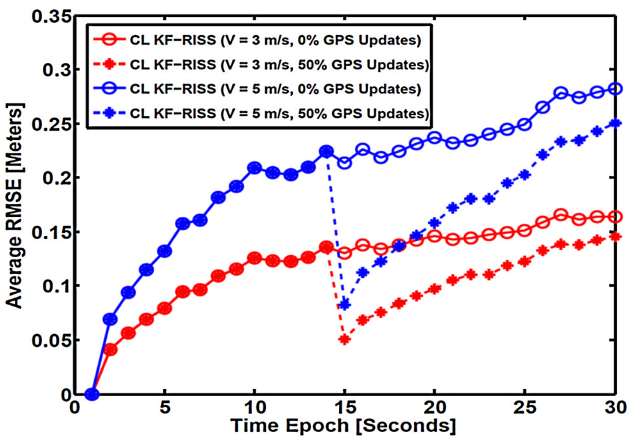

Fig. 8. Average RMSE of different percentage of ideal GPS updates on different velocities.

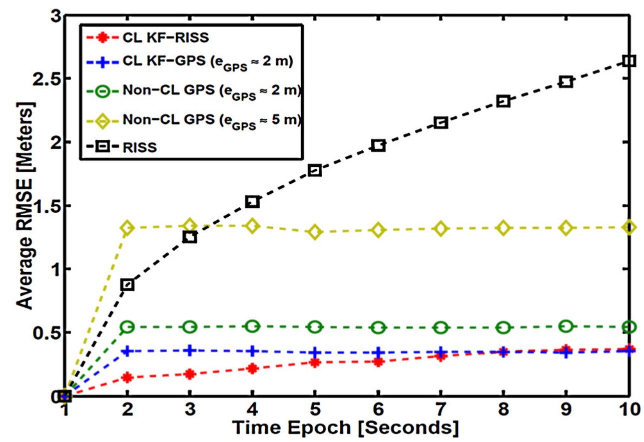

Fig. 10. Average RMSE comparison between the proposed cooperative scheme and the other existing localization systems.

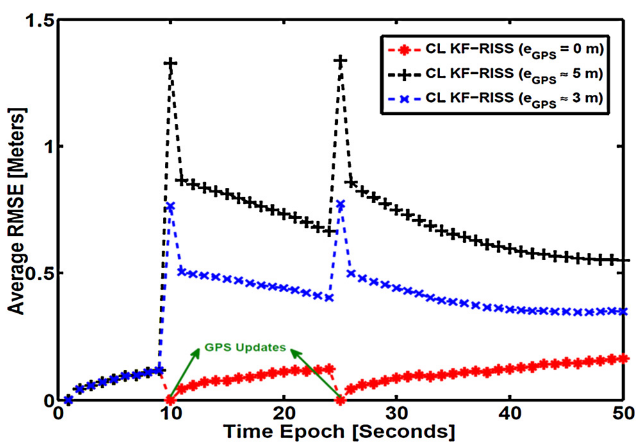

Fig. 9. Effect of erroneous GPS updates on the average RMSE.

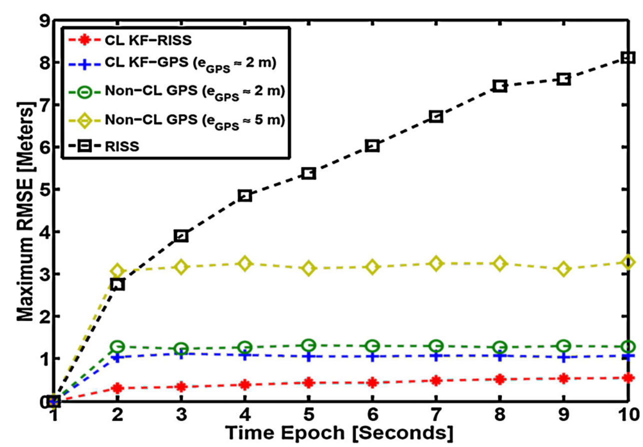

Fig. 11. Maximum RMSE comparison between the proposed cooperative scheme and the other existing localization systems.

enhance the proposed scheme performance only when the error variance of the GPS is less than the error variance of the RISS.

5.6. Comparison to mainstream localization schemes

The average of the RMSE and the maximum of the RMSE of the proposed cooperative scheme are compared with three other existing localization systems. The first is the non-cooperative RISS technique discussed before, the second is another non-cooperative scheme written in short as Non-CL GPS which is based on only having GPS positions with variances 0.22 and 1.39 that correspond to a maximum position errors of 2 m and 5 m, respectively. The third technique is a cooperative scheme to enhance GPS positions widely used in the literature [25] written here in short as CL KF-GPS. The CL KF-GPS scheme is updated in this work to have a similar structure and thus complexity to our introduced cooperative scheme. In essence, CL KF-GPS assumes that all the vehicles have open sky access, and thus the sender's and neighbors' positions are updated using GPS measurements instead of the RISS with variance 0.22 corresponding to a maximum error of 2 m.

In all the scenarios, the velocity of the vehicles is set to 11 m/s and the duration of the simulation to 10 seconds to guarantee that all the vehicles are in the communication range of each other and the only sources of the error are the sensors or GPS measurements irrespective of the density of neighboring vehicles. We recall that the proposed cooperative scheme localizes all vehicles using the RISS technique and then enhances these positions by cooperation with RTT-based range estimation. The sources of errors in this scheme are from the errors associated with the motion sensors (odometer and gyroscope) and the mechanization process.

Generally, the non-cooperative RISS scheme outperforms the non-cooperative GPS only for a very short term (i.e. 3 seconds in Fig. 10) while this is not the case for smaller GPS error variances that dominate for the whole duration. In addition, such duration becomes smaller with regards to the maximum RMSE as shown in Fig. 11. All the above is attributed to the typical accumulation of the large errors associated with the odometer in the high velocities.

Compared to the low noise GPS cooperative scheme, the introduced cooperative scheme based on the RISS only was able to extend the above short duration of the non-cooperative RISS beyond 10 seconds.

To summarize, the cooperative scheme was able to considerably stabilize the performance of the RISS which was found previously to deviate with time in the non-cooperative form. Thus, dependency on cooperative RISS for longer time duration can provide acceptable localization accuracy during complete GPS outages.

5.7. Cooperative scheme complexity

To assess the practicality of the proposed cooperative scheme, we compute its complexity. The first main block, LRM, in Fig. 2 has an $O(N^2)$ complexity as the vehicle will check the sender's ID in all the received messages, where N is the number of all the vehicles. This scenario corresponds to the worst case in which all the vehicles are requesting and responding to the LRM for all the vehicles in the system. As such, each vehicle should filter its own LRM responses and then decodes neighbors' information for the next stages.

The two stages of mechanization and distances calculations have lower complexity of $O(N)$. The mechanization is a linear operation that is done for all the responded $N-1$ neighbors and for the sender vehicle. Similarly, the calculation of both distances is done for all the $N-1$ neighbors. The EKF, in the final stage, comprises basic matrix operations such as inverse and multiplication with complexity of $O(N^3)$.

Both KF and EKF can be implemented by software or on FPGAs and then connected to the vehicle's on-board unit (OBU). Different implementations of KF in industrial applications were reviewed in [38]. Off-the-shelf smartphones are equipped with KF and can be used for data fusion and navigation [39,40]. Thus, a practical and cost-efficient EKF implementation in VANETs is attainable. The RISS algorithm and the KF-based implementation for the integration with GPS have been realized by our research group on a Xilinx FPGA board and tested on real – time [41].

6. Conclusion

In this paper, a cooperative localization technique is introduced to provide vehicles with high position accuracy in GPS-free environments. The scheme integrates the neighbors' updated positions using RISS mechanization with the measured inter-vehicle distances using RTT through EKF. This is in addition to adopting loosely coupled KF to update the RISS-based position with the GPS measurements when the vehicle has an open sky access. Error models were introduced to the motion sensors (odometer and gyroscope) and the GPS position updates for practical purposes. The scheme succeeded to limit the errors of the sensors, the neighboring vehicles positions and the mechanization process. Traffic traces were exported from SUMO and the scheme was implemented and tested on ns-3. Different scenarios were simulated to test the robustness of the proposed scheme for different velocities, vehicle densities, GPS availability and error models.

Firstly, the effect of different velocities as well as the accuracy of the initial position on the performance of the proposed cooperative scheme compared to the non-cooperative RISS technique is evaluated. The RMSE is larger for higher velocities because the error introduced to the odometer is a percentage of the vehicle's speed. For all values of velocity, the proposed cooperative scheme outperforms the RISS over the whole-time horizon due to the ability of the ranging technique to limit the error accumulation of the mechanization process. Secondly, the sensitivity levels for all the vehicles are increased to study the effect of the neighbors' densities on the RMSE. The results demonstrated the importance of extending the communication range of fast moving vehicles to cooperate with as many neighbors as possible and thus limit and compensate the large error of the mechanization.

Since vehicles can acquire GPS positions at certain time epochs, the performance of the cooperative scheme is only enhanced when the GPS error variance is less than the errors associated in the RISS within the proposed technique. Moreover, vehicles with GPS updated positions were able to share such enhancement among the network. Thus, decreased the RMSE of the surrounding neighbors with blocked GPS compared to the scenario of non-GPS updates in the network.

Furthermore, the proposed cooperative scheme, utilizing RISS under complete GPS outage, was compared to both the non-cooperative RISS and GPS as well as cooperative GPS-based scheme with different accuracies. Results demonstrated the ability of the proposed cooperative scheme to extend the reliability of RISS for a longer duration compared to the non-cooperative case. In particular, the cooperative scheme can outperform the low noise GPS cooperative scheme over a longer time duration compared to the non-cooperative forms of both techniques.

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