

Research Article

High Accuracy GPS-Free Vehicle Localization Framework via an INS-Assisted Single RSU

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Collision avoidance and road safety applications require highly accurate vehicle localization techniques. Unfortunately, the existing localization techniques are not suitable for road safety applications as they rely on the error-prone Global Positioning System (GPS). Likewise, cooperative localization techniques that use intervehicle communications experience high errors due to hidden vehicles and the limited sensing/communication range. Recently, GPS-free localization based on vehicle communication with a low cost infrastructure installed on the roadsides has emerged as a more accurate alternative. However, existing techniques require the vehicle to communicate with two roadside units (RSUs) in order to achieve high localization accuracy. In contrast, this paper presents a GPS-free localization framework that uses two-way time of arrival to locate the vehicles based on communication with a single RSU. Furthermore, our framework uses the vehicle kinematics information obtained via the vehicle's onboard inertial navigation system (INS) to further improve the accuracy of the vehicle location using Kalman filters. Our results show that the localization error of the proposed framework is as low as 1.8 meters. The resulting localization accuracy is up to 65% and 47.5% better than GPS-based techniques used without/with INS, respectively. This accuracy gain becomes around 73.3% when compared to existing RSU-based techniques.

1. Introduction

The growth in motor vehicle crashes and fatalities has recently caused safety applications for smart roads to receive significant attention to save millions of lives. According to the National Highway Traffic Safety Administration (NHTSA) in 2013, 5.4 million car crashes take place in average every year out of which 35,244 are fatal crashes. The average number of people killed on US roads each day is 80 and the estimated number of people injured in motor vehicle traffic crashes is 2.36 million. It is predicted that road crashes will be the fifth leading cause of death by 2030. In addition to such huge fatalities, billions of dollars are also lost every year in such crashes [1].

In order to develop robust road safety and collision avoidance systems, highly accurate vehicle localization techniques are needed. Many vehicle localization techniques have been recently proposed which can be broadly classified into absolute positioning techniques and relative positioning

techniques. In absolute positioning techniques, each vehicle has the ability to determine its own absolute location—without regard to nearby vehicles—based on using either Global Positioning System (GPS) [2–6] or roadside units (RSUs) [7–9]. Such positioning techniques are only applicable for navigation and fleet management application and are not well suited for collision avoidance applications. This is because of their low accuracy that can be up to tens of meters in GPS-based systems, the lack of lane-level positioning, and the discontinuous availability issues in the case of GPS-based techniques. On the other hand, relative positioning techniques use intervehicle communication and cooperative position approaches to determine the vehicles' locations relative to each other [6, 10–18]. However, cooperative localization techniques—which typically use either millimeter wave radar sensors or vision sensors—suffer not only from the limited sensing range and high cost of these sensors but also from the problems of hidden vehicles, slow update rates, and the multipath effect. Furthermore, lane-level vehicle localization

techniques which use vision-based lane-recognition systems suffer severe accuracy degradation in adverse weather conditions or in unclear lane signature situations [16–18].

In this paper, we present a highly accurate—yet low-cost—GPS-free integrated localization framework for collision avoidance and intelligent road safety applications. Unlike related works [7, 8] which typically use 2 roadside units (RSUs) for localization, our goal is to have each vehicle determining its location with respect to a single RSU in order to decrease the required number of RSUs and, consequently, reduce the cost of the localization system installation. The constraint of using a single RSU in vehicle localization poses a significant challenge in locating the vehicles with high accuracy. We use the vehicle kinematics information obtained through the inertial navigation systems (INS) and the road constraints broadcasted by RSUs to further improve the predictability and the accuracy in vehicle localization and provide lane-level localization accuracy.

The proposed localization framework consists of four stages: (1) determining the vehicle's driving direction, (2) estimating the distance between the vehicle and the RSU via two-way time of arrival (TOA) ranging to get an initial estimate of the vehicle location in the road length dimension, (3) obtaining a highly accurate estimate of the vehicle location in both the x - and y -dimensions by using Kalman filters to fuse the range obtained in the second stage and the vehicle kinematics information available through the vehicle's inertial navigation system, and (4) ensuring that the vehicle location in the road width dimension is within the physical boundaries of the road/lane which significantly improves the accuracy of the vehicle localization.

Our results show that the accuracy of the proposed single RSU localization framework significantly outperforms existing localization using GPS technique as well as existing RSU-based techniques. More specifically, our results show that the localization error of the proposed framework is as low as 1.8 meters. The resulting improvement in the localization accuracy is up to 65% and 47.5% compared to GPS-based techniques used without/with INS, respectively. This accuracy gain becomes around 73.3% when compared to existing RSU-based techniques.

The rest of the paper is organized as follows. In Section 2, we review the related literature. We present the system model in Section 3. In Section 4, we present our GPS-free vehicle localization framework. Then we evaluate the performance of the proposed framework in Section 5 and conclude the paper in Section 6.

2. Related Work

In this section, we overview the existing literature of positioning techniques that can be broadly classified into absolute positioning techniques and relative positioning techniques.

2.1. Absolute Positioning Techniques

2.1.1. GPS-Based Absolute Positioning. Such positioning approach uses the Global Positioning System (GPS) to

determine the position of each vehicle. The traditional GPS localization technique [2] uses GPS receivers to continuously receive the data being sent by the GPS satellites. The received data is used to estimate the vehicle's distance to at least four known satellites using a technique called time of arrival (TOA) and then computes the actual position via trilateration.

GPS-based techniques suffer many challenges. One main challenge is the low accuracy of GPS systems (10 m–30 m) that is not sufficient for vehicle collision warning systems. Therefore, several modifications of the basic GPS technique have been proposed to increase the accuracy of GPS-based localization. An example of such methods is the radio-frequency-GPS (RF-GPS) [3] that employs a differential GPS (DGPS) concept to improve the GPS accuracy. DGPS [19] is a method to improve the positioning of GPS using one or more reference stations at known locations, each equipped with at least one GPS receiver. The reference station(s) calculates the error and broadcasts it.

Another problem in GPS-based techniques is the existence of tall buildings which prevent the GPS receivers on vehicles from receiving strong satellite signals. Assisted-GPS (A-GPS) has been proposed to enhance the performance of standard GPS in devices connected to the cellular network by using an A-GPS server [4]. Although there exist some enhanced versions of GPS such as the A-GPS and RF-GPS, they require extra infrastructures and, hence, add cost.

2.1.2. GPS-Free Absolute Positioning. The need for GPS-free localization techniques comes from the facts that the accuracy of GPS positioning algorithms (with localization error between 10 m and 30 m) are not accurate enough for collision warning system applications. Thus motivated, new techniques using roadside units (RSUs) [7–9] have been proposed to eliminate the need to use GPS techniques. RSUs are installed on both sideways of the road and all the vehicles are equipped with onboard unit (OBU) devices that are able to communicate with the RSUs. Hence, each vehicle has the ability to estimate its coordinates relative to the RSUs. The author of [7] assumed that there are two RSUs installed on both sides of the road and each vehicle estimates its location relative to those two RSUs using a technique called *faulty-free*. The author in [7] also illustrates another scenario, called *faulty*, in which one of the RSUs fails such that only one RSU remains functional.

Alternatively, the proposed approach in [8] depends on obtaining the initial position using single RSU information and updates the position *all the way* using dead reckoning. Dead reckoning [7] is a technique that is originally used for localization in the absence of GPS coverage in GPS-based techniques which is an effective alternative to inter-vehicle communications techniques [10, 11]. However, the accumulation of dead reckoning error makes the localization accuracy of [8] significantly deteriorate with distance as we shall demonstrate in the simulation results. The localization approach in [8] does not use any distance-measuring techniques such as time of arrival (TOA) [20], time difference of arrival (TDOA) [21], and received signal strength (RSS) [11].

Thus motivated, the authors of [9] proposed to use TOA-based distance-measuring to significantly reduce the positioning error and restrict the use of the erroneous dead reckoning to the close proximity of the RSU.

2.2. Relative Positioning Techniques. All of the above absolute positioning techniques are not suitable for collision avoidance applications due to their limited accuracy. Furthermore, such techniques are not capable of determining the lane in which the vehicle is traveling. Hence, they are not applicable to collision avoidance systems in which a vehicle has to accurately know its relative distance with the neighboring vehicles. Relative positioning techniques have emerged to improve the positioning accuracy by having the vehicles exchanging their erroneous location information and jointly cooperate to reach a more accurate positioning relative to each other. Such cooperative techniques [10–15] estimate intervehicle distances using either RSS [11], time of arrival (TOA) [12], both of RSSI and two-way TOA [10], millimeter wave radar sensors [13], vision-based sensors [14], or Doppler shift [15] as an intervehicle ranging technique.

2.2.1. GPS-Based Relative Positioning. Several existing relative positioning techniques rely on GPS as an input to the localization process. Examples include the Intervehicle-Communication-Assisted Localization (IVCAL) which uses a Kalman filter (KF) to fuse the positioning information obtained by both GPS and the inertial navigation system (INS). The KF-fused position and the relative distance estimation, obtained from intervehicle communication, are integrated using least square optimization in order to increase the accuracy of the localization of every vehicle in the network. Likewise, the grid-based on-road localization (GOT) system was developed to use vehicle cooperating to allow vehicles with blocked GPS signal, for example, when the vehicles are inside a tunnel or on a road surrounded by high rises, to accurately calculate their position through the help of at least three vehicles with good GPS signals using intervehicle distance estimation.

2.2.2. GPS-Free Relative Positioning. In order to improve the predictability and the accuracy in vehicle localization, several works have been carried out to develop GPS-free cooperative vehicle localization schemes that do not rely on any form of GPS assistance [10, 11, 14]. For instance, [11] proposed a three-phase localization technique in which each vehicle initially estimates the intervehicle distances with its neighbors using RSSI. After sharing such information with neighboring vehicles, each vehicle improves its estimation alongside the vehicle kinematics and road constraints information using Kalman filter [22]. The process is iterated periodically to maintain an up-to-date estimate of the vehicle position. Meanwhile, the authors of [14] proposed a two-phase GPS-free neighbor-vehicle mapping framework that has each vehicle fetching the neighboring vehicles' presence/absence status information from a vision-based environment sensor system that covers a specific calibrated region in the front, back, and adjacent left/right lanes of the vehicle using omnivision

camera-based sensor systems. After exchanging this status information with neighbor vehicles, each vehicle builds a relative local map that links the neighbors' information and their communication addresses, such as Medium Access Control/Internet Protocol (MAC/IP), with the vehicles' cardinal locations.

GPS-based positioning techniques suffer from many problems that degrade the localization accuracy including multipath and signal blocking with high buildings and during moving through tunnels. In contrast, our proposed localization technique is based on using RSUs for localization to improve the accuracy and the complexity of the existing node localization algorithm. We also exploit fusion techniques developed for relative positioning to further increase the localization accuracy. However, we only rely on the vehicle's own information only without any kind of intervehicle information.

3. System Model

In our system model, vehicle localization is not based on GPS receivers. Instead, we assume that all vehicles are equipped with onboard unit (OBU) devices that are used to determine the vehicle's distance to the RSUs using vehicle-to-road (V2R) communication. We use the dedicated short-range communications (DSRC 5.9 GHz) for intelligent transportation systems over which the IEEE 802.11p operates. We exploit RSUs deployed only on one side of the road to locate the vehicles. The RSUs broadcast periodic beacons containing the ID of the road and the location of the RSU. For collision avoidance, we assume that the neighboring vehicles exchange their locations using vehicle-to-vehicle (V2V) communication. However, we do not use V2V communication for the localization process itself, and, hence, V2V communication falls behind the scope of the paper.

Each vehicle is equipped with a digital odometer, a compass, and an inertial navigation system (INS) which are commonly available devices in modern vehicles. INS is a navigation technique used to get the current position of an object relative to a previous position by measuring the velocity and orientation of the object. The most common sensors used to get the previous measurements are accelerometers and gyroscopes that provide the velocity and the direction information, respectively.

We assume that vehicles move on dual carriageway highway separated by a central reservation. The road is straight all the way and there are multiple entry and multiple exit points along the road. Such a road model is widely adopted in the related literature. Each entry point is equipped with an RSU. We assume that the entry/exit points are interleaved (i.e., at a given y -location, we can have only one entry to the road with an exit on the other side) as the typical case depicted in Figure 1. The road has shoulders that a vehicle can use to reverse the driving direction. However, the road does not have any intersections. We assume that the distance between the RSU and the vehicle R is large and the width of the road W is too small compared to its length L , and, hence, the curvature is assumed to be nearly linear. The Notations summarizes the used notations.

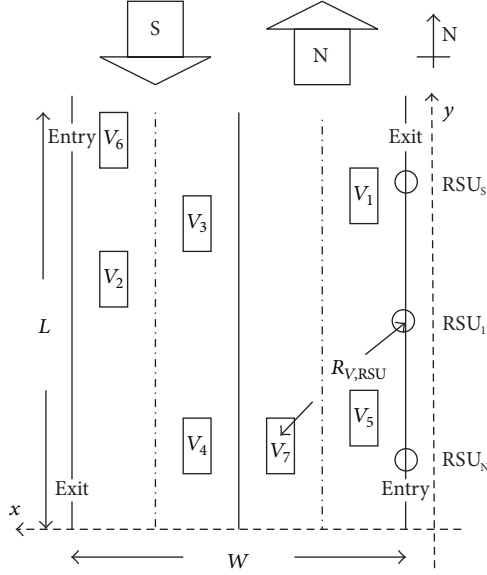


FIGURE 1: Illustration of the system model.

4. GPS-Free Vehicle Localization Framework via an INS-Assisted Single RSU

We introduce a GPS-free localization framework that only uses (1) a single RSU for locating the vehicle along the road length (y -dimension) and (2) INS information with Kalman filtering to accurately specify the lane-level location of the vehicle (x -dimension). The vehicle location is constrained by the road boundaries broadcasted from the RSU which contain information about the geometry of the road such as width of the road and number of lanes. Each vehicle then shares its computed location information using V2V communications with nearby vehicles to be used for collision avoidance systems. However, this paper is only concerned with determining the location of the individual vehicles.

The proposed framework consists of four main components: (1) determining the vehicle's driving direction which is either north (N) or south (S), (2) measuring the distance between the vehicle and the nearest RSU, $R_{V,RSU}$, using two-way TOA, (3) estimating the vehicle location (\hat{x}, \hat{y}) using $R_{V,RSU}$ estimated from the previous component and the INS information locally provided by the vehicle, and finally (4) ensuring that the final vehicle location \hat{x}_k is within the road/lane boundaries obtained from the periodic beacons broadcasted from the RSUs using a road boundary stage. Figure 2 summarizes the proposed framework. We next explain the details of each of the four main components of the framework.

4.1. Determining the Vehicle Driving Direction. This section discusses our proposed technique to find the driving direction. In [7] a technique for determining the driving direction using two roadside units installed on both sides of the road has been proposed. A vehicle determines its driving direction by comparing the angle between its current movement vector

and the north (or south) roadside unit. Meanwhile, the authors in [8] assume that there are RSUs installed on one side of the road and each vehicle should receive and evaluate the position information of 2 consecutive two RSUs to get the driving direction. Given our system model, the major challenge here is how to get the driving direction with the help of only one RSU installed on one road direction and minimize the start-up time.

We propose the following algorithm which is invoked every time the vehicle enters a new road to decide the direction the vehicle is traveling. Without loss of generality, we denote the travel direction as either north (N) or south (S) to distinguish the two travel possibilities. However, the absolute travel direction is obtained by interpolating the RSU well-defined coordinates which are exactly known and broadcasted to all vehicles. We first assume that there are two types of roadside units: one type which is at the entry points of the road. The second type of RSUs is in the middle of the road between the entry points. We assume that an entry RSU broadcasts the driving direction either N or S while a middle RSU has a Null direction field in its beacon. When a vehicle first enters the road, it will determine its driving direction based on the direction of the first beacon received from an entry RSU. As the vehicle moves along the road, it receives a beacon from a middle RSU which contains the ID and the location of the RSU. The driving direction is updated to be either the same or the opposite direction based on the ID of the new RSU (included in the incoming beacon) and the ID of the previous RSU (stored on the OBU which is initially set to Null). Therefore, even if the vehicle make a U-turn using the shoulder, comparing the new received RSU ID with the ID stored on the OBU will allow the vehicle to know that the driving direction has been switched. Algorithm 1 outlines the proposed algorithm assuming that the RSU ID increases in the north direction.

It is worth mentioning that Algorithm 1 can be easily generalized to vehicle localization in intersected roads. In such a case, the intersection points should be equipped with RSUs that broadcast all four possible travel directions: the legacy directions N and S, as well as two perpendicular directions such as east (E) and west (W). The intersection RSUs are treated as entry/exit points of the perpendicular road. When the vehicle receives a beacon from such an intersection RSU, it checks whether the driving direction is the same or has been switched to the perpendicular direction. However, intersected roads fall behind the scope of this paper.

4.2. Estimating the Vehicle Distance to the RSU (Ranging). The goal of this stage is to estimate the y -location of the vehicle based on estimating the distance between the vehicle and the RSU, $R_{V,RSU}$, using V2R communication. In our proposed RSU-based localization scheme, each vehicle estimates its distance to the RSU upon receiving the RSU periodic beacon messages which contain the ID of the RSU and its Y -coordinate denoted by L_{RSU} . As shown in Figure 1 and given that the RSU is located at location L_{RSU} , a vehicle V is located at

$$\bar{y} = L_{RSU} \pm R_{V,RSU}, \quad (1)$$

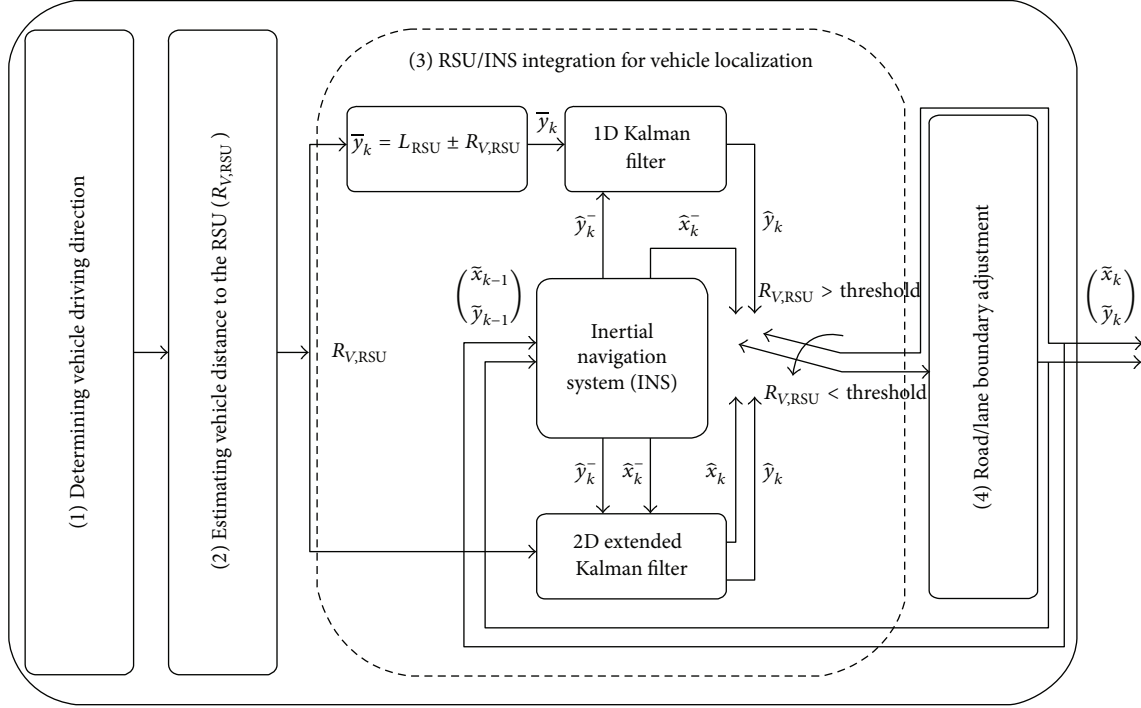


FIGURE 2: The proposed GPS-free integrated framework for vehicle localization using a single RSU and INS information.

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(1) Initialization: Driving Direction = NULL
(2) if Receive(Beacon) and Beacon.Direction  $\neq$  NULL then
(3)   Driving Direction = Beacon.Direction
(4)   Current RSU = Beacon.ID(RSU)
(5) else
(6)   if Beacon.ID(RSU) > Current RSU then
(7)     Driving Direction = North
(8)   else
(9)     Driving Direction = South
(10)  end if
(11)  Current RSU = Beacon.ID(RSU)
(12) end if

```

ALGORITHM 1: Algorithm for driving direction determination.

where $R_{V,RSU}$ is the distance between the RSU and vehicle V . The sign of $R_{V,RSU}$ depends on the driving direction obtained in the previous stage and whether $R_{V,RSU}$ tends to increase or decrease.

It is worth mentioning that (1) is only valid under the assumption that the distance between the RSU and the vehicle is large enough and the width of the road is too small compared to its length, and, hence, the curvature is assumed to be a line as per our system model. When the vehicle moves closer to the RSU, this assumption is no longer valid. Therefore, the proposed ranging technique is used to provide an estimate of the y -location of the vehicle to be refined in

the next stage only when $R_{V,RSU}$ is greater than a certain threshold and we will use another technique when $R_{V,RSU}$ is less than that threshold as will be discussed in Section 4.3.

Many techniques are used for range measurements such as received signal strength (RSS) [11], angle of arrival (AoA) [23], time difference of arrival (TDOA) [21], and time of arrival (TOA) [20]. In our proposed technique, we use the two-way reciprocal time of arrival [24] technique which is preferred in the presence of multipath interference and does not need synchronization between the transmitter and the receiver. Recall that DSRC systems should be resilient to multipath fading [25]. The proposed two-way reciprocal

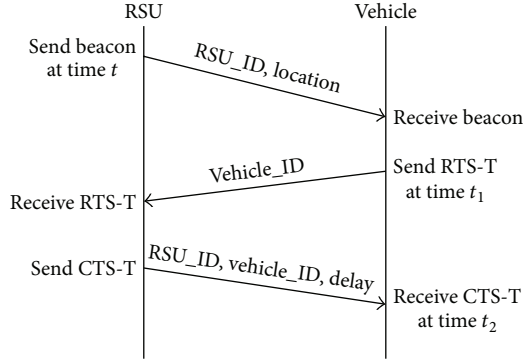


FIGURE 3: The timeline of the proposed two-way TOA packet handshake.

time of arrival technique works as follows. When the vehicle receives a beacon from the RSU, the vehicle will send a request to send for two-way TOA (RTS-T) packet at time t_1 . The RSU will reply with a clear to send two-way TOA (CTS-T) packet which contains the delay τ experienced at the RSU (which might come from collisions and processing time). The CTS-T is received at the vehicle at time t_2 as shown in Figure 3. The difference between the time the CTS-T is received and the time the RTS-T is sent is equal to the propagation time of the RTS-T plus the processing delay(s) within the RSU plus the propagation time of the CTS-T; that is,

$$t_2 - t_1 = \frac{R'_{V,RSU}}{C} + \tau + \frac{R_{V,RSU}}{C}, \quad (2)$$

where $R'_{V,RSU}/C$ and $R_{V,RSU}/C$ are the propagations times of the RTS-T and CTS-T packets, respectively, and C is the free-space propagation speed. Equation (2) can be rewritten as

$$(t_2 - t_1 - \tau)C = R_{V,RSU} + R'_{V,RSU}, \quad (3)$$

where $R_{V,RSU}$ is the distance between the RSU and the vehicle at instant t_2 and $R'_{V,RSU}$ is the distance between the RSU and the vehicle at instant t_1 , as shown in Figure 4. Recall that the x distance between the vehicle and the road side is negligible with respect to $R_{V,RSU}$ and $R'_{V,RSU}$ as per the assumed system model. Hence, the vehicle displacement can be approximated with an increment/decrement in the y -direction, depending on whether the vehicle is moving away/towards the RSU; that is,

$$R'_{V,RSU} \cong R_{V,RSU} \pm \Delta y. \quad (4)$$

Substituting with $R'_{V,RSU}$ given in (4) into (3), we get

$$(t_2 - t_1 - \tau)C = 2R_{V,RSU} \pm \Delta y. \quad (5)$$

Consequently, the y -location of the vehicle y_V given in (1) is computed using $R_{V,RSU}$ given by

$$R_{V,RSU} = \frac{(t_2 - t_1 - \tau)C + \Delta y}{2}, \quad \Delta R > 0, \quad (6)$$

$$R_{V,RSU} = \frac{(t_2 - t_1 - \tau)C - \Delta y}{2}, \quad \Delta R < 0,$$

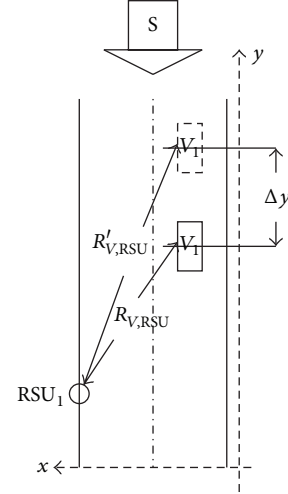


FIGURE 4: Range estimation using two-way TOA.

where $\Delta R = R_{V,RSU}(i+1) - R_{V,RSU}(i)$ and $R_{V,RSU}(i)$ is the estimated range after receiving the i th beacon from the RSU, determining whether the vehicle is approaching or moving away from the RSU. The only unknown in the above equations is Δy . A vehicle locally computes Δy as $\Delta y = (t_2 - t_1)v$, where v is the average vehicle speed. Hence, our proposed ranging technique computes the y -location of the vehicle using a single RSU.

4.3. RSU/INS Integration for Vehicle Localization. In the second stage of the proposed framework, we have only obtained an estimate \bar{y} of the y -location of the vehicle relative to the nearest RSU. The goals of this stage of the proposed framework are to (1) refine the y -location estimate, \bar{y} , outside the threshold area, (2) estimate the y -location of the vehicle within the threshold area, and (3) estimate the x -location of the vehicle, \bar{x} . In other words, this stage not only is responsible for significantly improving the accuracy of our ranging technique but also enables the framework to capture the lane-level information required for the targeted collision avoidance applications.

Our approach is to use data fusion techniques such as Kalman filter that is widely used to enhance the vehicle location obtained from GPS receivers [11, 26, 27]. Unlike such techniques which integrate the readings from both GPS receivers and the vehicle's inertial navigation system (INS) to form an estimate of the vehicle location, we use different types of Kalman filters to either enhance the y -location obtained from our single RSU ranging approach, \bar{y} , and the y -location obtained from INS or obtain the x -location and the y -location in the region in which the RSU-based ranging is not applicable.

For vehicles moving outside the threshold area, the y -location, \bar{y} , is linearly related to $R_{V,RSU}$, and, hence, it can be directly fused with the y -location of the INS. This is not the case for the x -location. Unfortunately, we have only one input for x -location which is obtained from INS and do not have other sources for x -location data that is linearly

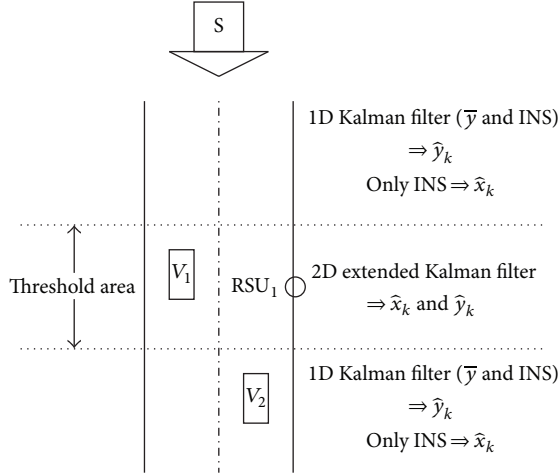


FIGURE 5: An illustration of the various fusion techniques used along the road. Vehicles V_1 and V_2 are inside and outside the threshold area, respectively.

related to x . Hence, we cannot use two-dimensional Kalman filter to simultaneously enhance the y -location and get the x -location. Therefore, we use a one-dimensional Kalman filter to refine the y -location and rely only on the INS information to update the x -location when $R_{V,RSU} > \text{threshold}$.

For vehicles moving inside the threshold area around the RSU, where there is no linear relation between $R_{V,RSU}$ and the vehicle location, we use a nonlinear version of the Kalman filter (extended Kalman filter) which linearizes the measurement $R_{V,RSU}$ around the current estimate. In this case, the range $R_{V,RSU}$ is considered as one input of the extended Kalman filter instead of y -location \bar{y} and INS is the other input of the extended Kalman filter. Note that the performance of the extended Kalman filter results in slightly worse accuracy in the y -location compared to the one-dimensional Kalman filter since the Kalman filter is an optimal estimator for linear measurement and process equations [22]. Figure 5 summarizes the various localization techniques used inside and outside threshold area. The threshold—depicted in Figure 5—is computed using the target localization error as will be shown in Section 5. We next briefly overview the fundamentals of Kalman filters and then explain in detail how they are used in the proposed localization approach.

4.3.1. Kalman and Extended Kalman Filters Preliminaries.

In the proposed localization approach, the Kalman and extended Kalman filters use a vehicle's motion model—obtained from INS—and the sequential measurement—obtained from RSU-based localization technique—to form an estimate of the vehicle location that is better than the estimate obtained by using only one measurement (either INS or the proposed RSU-based localization) alone. The motion model of the vehicle obtained from INS, also referred to as the system process model, is expressed as follows:

$$\underline{\varphi}_k = A\underline{\varphi}_{k-1} + B\underline{u}_{k-1} + \underline{w}_{k-1}. \quad (7)$$

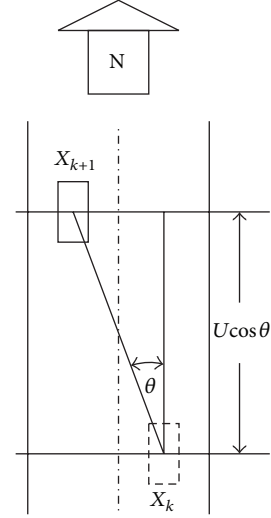


FIGURE 6: INS vehicle kinematics.

The process equation in (7) represents the estimation of the current vehicle location $\underline{\varphi}_k$ based on the previous location $\underline{\varphi}_{k-1}$ using the INS, where $\underline{\varphi}_k$ is the 2×1 vector that represents the vehicle location (x, y) at time t_k . The process noise \underline{w}_k is a random vector which is modeled as Gaussian random variable with zero mean and covariance matrices Q ; that is, $\underline{w}_k \sim N(0, Q)$. \underline{u}_k is a 2×1 vector that represents vehicle velocity components in the x - and y -directions which is calculated as

$$\underline{u}_k = v \begin{bmatrix} \cos(\theta) \\ \sin(\theta) \end{bmatrix}, \quad (8)$$

where v is the vehicle speed and θ is the angle between the y -axis and the vehicle motion direction as shown in Figure 6. The process equation given by (7) applies a state transition model, reflected by the A matrix, to the previous state $\underline{\varphi}_{k-1}$ and applies a control-input model, reflected by the B matrix, to the control vector \underline{u}_k . The A and B matrices are defined as follows:

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad (9)$$

$$B = \begin{bmatrix} T & 0 \\ 0 & T \end{bmatrix},$$

where T is the time interval.

On the other hand, the measurement model that is derived from the INS data can be expressed as

$$\hat{\underline{\varphi}}_k^- = A\hat{\underline{\varphi}}_{k-1} + B\underline{u}_k, \quad (10)$$

where $\hat{\underline{\varphi}}_k^-$ is the a priori state estimate of the vehicle location and $\hat{\underline{\varphi}}_k$ is the a posteriori state estimate of the vehicle location. For the one-dimensional Kalman filter, we use the second component of $\hat{\underline{\varphi}}_k^-$ which represents the vehicle's

y -location obtained from INS. On the other hand, for the two-dimensional extended Kalman filter, we use the two components of INS $\hat{\phi}_k^-$ which reflect both the x - and y -locations of the vehicle. The Kalman and extended Kalman filters integrate the system process and measurement models to result in a more accurate estimate of the vehicle location.

4.3.2. One-Dimensional Kalman Filter for Locating Distant Vehicles. As explained earlier, we divide the localization of vehicles into two regions: one in which $R_{V,RSU}$ is greater than a certain threshold and another when $R_{V,RSU}$ is below that threshold. Here, we obtain the vehicle location for distant vehicles when $R_{V,RSU}$ is greater than the threshold, and, hence, \bar{y} is linearly related to the actual y -location of the vehicle. In order to get an accurate vehicle location that fits collision warning system applications, the initially obtained y -location from the second stage of the framework \bar{y} is enhanced using a one-dimensional Kalman filter, and we only rely on the INS data to determine the x -location of the vehicle.

For the process model of the one-dimensional Kalman filter, the vehicle uses its y -location obtained from INS, which is the second element of the vector $\hat{\phi}_k^-$, that is, $\hat{\phi}_k^-(2, 1)$. In addition, the one-dimensional Kalman filter uses the vehicle's estimate of its y -location obtained via the second stage of the framework \bar{y}_k . However, the estimate \bar{y}_k is prone to measurement noise resulting from the range-based localization technique used in our single RSU-based localization technique. Such a measurement noise consists of the noise in the estimation of the range between the vehicle and the RSU, n_R , and the curvature noise ε_k that reflects the lane-level ambiguity inherited from approximations assumed in (1). The curvature error is negligible compared to the noise in the range distance estimation n_R . The effect of the curvature error is investigated in Section 5. To capture such measurement noise components, we use

$$z_k = \bar{y}_k + \zeta_k \quad (11)$$

as the other estimate of the vehicle's y -location fed to the one-dimensional Kalman filter, where \bar{y}_k is the estimated vehicle location using our RSU-based approach at time t_k , and ζ_k is a random vector which is considered to be Gaussian with zero mean and variance σ_r^2 to model the measurement noise; that is, $\zeta \sim N(0, \sigma_r^2)$, where

$$\zeta_k = n_r + \varepsilon_k. \quad (12)$$

Two distinct sets of equations describe the operation of the Kalman filter: time update (prediction) and measurement update (correction) equations. Both equation sets are applied at the k th iteration when the vehicle is moving outside the threshold area where $R_{V,RSU} > \text{threshold}$. The time update (prediction) equations of the proposed one-dimensional Kalman filter are given by

$$\begin{aligned} \hat{y}_k^- &= \hat{\phi}_k^-(2, 1), \\ p_k^- &= p_{k-1} + q. \end{aligned} \quad (13)$$

Meanwhile, the corresponding measurement update (correction) equations are given by

$$\begin{aligned} g_k &= \frac{p_k^-}{p_k^- + \sigma_r^2}, \\ \hat{y}_k &= \hat{y}_k^- + g_k (z_k - \hat{y}_k^-), \\ p_k &= (1 - g_k) p_k^-, \end{aligned} \quad (14)$$

where \hat{y}_k^- is the a priori state estimate of the vehicle location, \hat{y}_k is the a posteriori state estimate of the vehicle location, g_k is the Kalman gain, p_k is the a posteriori estimate error variance, and p_k^- is the a priori estimate error variance. Since the Kalman filter at hand is one-dimensional, all the entities in the above model, such as A and B in (7) and (10), are scalars.

We use INS to get the current x -location of the vehicle related to the previous one which is the first component of $\hat{\phi}_k^-$, obtained from (10). The final vehicle location outside the threshold area where $R_{V,RSU} > \text{threshold}$ is given by

$$\hat{\phi}_k = \begin{bmatrix} \hat{\phi}_k^-(1, 1) \\ \hat{y}_k \end{bmatrix}. \quad (15)$$

Recall that vehicles always enter the road through entry points as shown in our system model depicted in Figure 1. Hence, we set the initial estimate at $k = 0$ of the two components of $\hat{\phi}_0$ to the center of the first lane and 0, respectively, and set p_0 to 0.

It is worth mentioning that using the inertial navigation system alone to get x -location will result in an accumulation of the positioning error with time. However, this is the only way we can get information about the x -location of the vehicle given that distant vehicle localization in the second stage of the framework is based on the assumption that the road width is too small compared to its length.

4.3.3. Two-Dimensional Extended Kalman Filter for Locating Nearby Vehicles. Next, we estimate the vehicle location using two-dimensional extended Kalman filter in the region in which $R_{V,RSU}$ is below the threshold where the Kalman filter can no longer be used due to the nonlinear relationship between $R_{V,RSU}$ and the vehicle location. Similar to the Kalman filter, the extended Kalman filter integrates measurement and process models. Instead of using the linear output \bar{y} in the measurement model given in (11), we use the nonlinear estimation of the range between vehicle and the RSU, $R_{V,RSU}$, inside the threshold area. Hence, z_k —which represents the estimated range between the vehicle and roadside unit—is expressed inside the threshold area as follows:

$$z_k = h(\phi) + n_r, \quad (16)$$

where $h(\cdot)$ is a nonlinear function of the two components of the vehicle locations ϕ , x , and y that is used to compute the predicted single-value measurement from the predicted state ϕ as

$$h(\phi) = \sqrt{(x - x_{RSU})^2 + (y - y_{RSU})^2}, \quad (17)$$

where (x, y) is the vehicle location. The measurement noise $n_r \sim N(0, \sigma_r^2)$ in (16) comes from the single RSU-based localization technique proposed in the second stage of the framework. Unlike the case of $R_{V,RSU} > \text{threshold}$, n_r here only represents the noise in the estimation of the range between the vehicle and the RSU, $R_{V,RSU}$.

Unlike the system process in the one-dimensional Kalman filter which only uses the second component of $\hat{\varphi}_k^-$: $(\hat{\varphi}_k^-(2))$, we use the two components of $\hat{\varphi}_k^-$ in the two-dimensional Kalman to represent the estimation of complete vehicle location using the INS. The time update (prediction) and measurement update (correction) equations applied at the k th iteration when $R_{V,RSU} < \text{threshold}$ are given by

$$P_k^- = AP_{k-1}A^T + Q, \quad (18)$$

$$\underline{g}_k = P_k^- \underline{h}_k^T (h_k P_k^- \underline{h}_k^T + \sigma_r^2)^{-1}, \quad (19)$$

$$\hat{\varphi}_k = \hat{\varphi}_k^- + \underline{g}_k (z_k - h(\hat{\varphi}_k^-)), \quad (20)$$

$$P_k = (I - \underline{g}_k \underline{h}_k) P_k^-, \quad (21)$$

respectively, where $\hat{\varphi}_k^-$ is the 2×1 a priori state estimate of the vehicle location, $\hat{\varphi}_k$ is the 2×1 a posteriori state estimate of the vehicle location, \underline{g}_k describes the 2×1 Kalman gain, P_k is the 2×2 a posteriori estimate error covariance matrix, P_k^- is the 2×2 a priori estimate error covariance matrix, Q is the 2×2 covariance matrix of the process noise, I is the 2×2 unit matrix, and \underline{h}_k is the 1×2 Jacobian vector of the partial derivatives of $h(\varphi)$ with respect to φ that is evaluated with the current predicted state at each iteration k ; that is,

$$\underline{h}_k = \left. \frac{\partial h(\varphi)}{\partial \varphi} \right|_{\hat{\varphi}_k^-} = \left[\frac{\partial h(\varphi)}{\partial x} \quad \frac{\partial h(\varphi)}{\partial y} \right]_{\hat{\varphi}_k^-}. \quad (22)$$

4.4. Road/Lane Boundary Adjustment Stage. The erroneous estimate of the vehicle's x -location obtained in the above stage of the framework is prone to fall outside the physical boundaries of the road. This is unacceptable for the targeted collision avoidance systems. In order to ensure that the output \hat{x}_k falls within the road boundaries, the output of the vehicle localization stage is adjusted according to the road boundaries stage. This final stage uses the road geometry information loaded from the periodic beacons broadcasted by the RSUs. The road boundary adjustment stage fixes the x -location of each vehicle to be

$$\Delta \tilde{x}_k \leq d, \quad (23)$$

where $\Delta = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$ and d depends on the geometry of the highway. Typically, d is set to be equal to $\begin{bmatrix} W \\ 0 \end{bmatrix}$, where W is the width of the road, such that the x -location of the vehicles is limited to the road boundaries that are at 0 and W . However, this typical value of d does not guarantee the lane-level accuracy required for collision avoidance systems. Therefore, we set the d to the lane boundaries instead of

the road boundaries which significantly improves the accuracy in estimating the x -location of the vehicles as will be shown in Section 5. Recall that the road geometry information broadcasted by the RSU includes the number of lanes per road as well as the road width, and, hence, the lane width information is available to the vehicles.

Let L_i denote the boundary of the i th lane and L_0 is equal to zero. If the vehicle is moving in the i th lane, \tilde{x}_k must lie between L_{i-1} and L_i ; that is,

$$L_{i-1} < \tilde{x}_k \leq L_i. \quad (24)$$

Substituting with L_{i-1} and L_i for the values of d in (23), we obtain a set of inequalities that are considered as an active set problem where only set of the constraints is active at a time. We use both moving average and exponentially weighted moving techniques to estimate the current lane. By knowing the current lane, the estimated x -location after applying the road boundary, \tilde{x}_k , is checked against the lane boundary. The road and lane constraints can be summarized as follows:

$$\tilde{x}_k = \begin{cases} 0, & \text{if } \hat{x}_k \leq 0, \\ W, & \text{if } \hat{x}_k \geq W, \\ L_{i-1} \leq \tilde{x}_k \leq L_i, & \text{if current lane} = \text{Lane } i. \end{cases} \quad (25)$$

In order to determine the current lane at time instant k , we first calculate the moving average, MA_k , of the M prior observations of \tilde{x}_k ; that is,

$$MA_k = \sum_{i=k-M}^{k-1} \frac{\tilde{x}_i}{M-1}. \quad (26)$$

Second, we use the exponential weighted moving average to smooth out short-term fluctuations and prevent wrong lane determination. We calculate the exponential weighted moving average, EMA_k , of the M prior observations including the current observation as follows:

$$EMA_k = \alpha EMA_{k-1} + (1 - \alpha) \tilde{x}_k, \quad (27)$$

where EMA_{k-1} is the a priori exponentially weighted moving average and $0 < \alpha \leq 1$ is the weighting factor. Then, we compare the difference between EMA_{k-1} and MA_k to a certain value called the change-lane-threshold (CLT) to decide whether the vehicle has changed its lane or not.

4.5. Framework Integration. By the end of the aforementioned four stages of the proposed framework, each vehicle has an accurate estimate of its own location only. In order to share the vehicle location of neighbor vehicles to be used for the targeted collision avoidance applications, we assume that vehicles will be using V2V communications to share their location, travel direction, and speed with the nearby vehicles. This will allow the collision avoidance system to take the appropriate action(s) to avoid a large amount of crashes and provide the vehicle driver with warnings to avoid rear-end, lane change, and intersection crashes.

Our proposed framework can be summarized as follows.

Step 1. Each RSU broadcasts beacons at periodic time instants which contain the ID of the RSU, the location of the RSU, and the road geometry information.

Step 2. Each vehicle determines its driving direction which can be either north (N) or south (S) every time the vehicle enters a new road, as illustrated by Algorithm 1.

Step 3. Each vehicle determines its range to the RSU $R_{V,RSU}$ using the proposed two-way TOA ranging technique.

Step 4. Each vehicle uses the range $R_{V,RSU}$ estimated in Step 3 to get the y -location \bar{y} when $R_{V,RSU} > \text{threshold}$, where there is a linear relationship between the y -location and the range $R_{V,RSU}$.

Step 5. Each vehicle uses one-dimensional Kalman filter to get a refined y -location \hat{y}_k when the $R_{V,RSU} > \text{threshold}$ and uses INS to obtain/update x -location \hat{x}_k .

Step 6. Each vehicle uses two-dimensional extended Kalman filter when $R_{V,RSU} < \text{threshold}$ to get both the x - and y -locations. We reinitialize x -location in the threshold area when the vehicle is exactly at the x -location of the RSU.

Step 7. In order to ensure that the output $\hat{\underline{p}}_k$ from Step 6 is within the road/lane boundaries, $\hat{\underline{p}}_k$ is adjusted through the road boundary adjustment stage.

Step 8. Each vehicle broadcasts its position calculated from Step 7 to its neighbors using V2V communications.

Step 9. Periodically repeat the above steps.

5. Simulation Results

We evaluate the performance of the proposed framework using MATLAB simulations. We assume that vehicles move on a dual carriageway highway; each direction has three lanes, separated by a central reservation. The road is straight line. The length of the road is 3 km, and 3 RSUs are used; each has a 500 m communication range: south RSU (placed at $y = 500$ m), north RSU (placed at $y = 1500$ m), and middle RSU (placed at $y = 2500$ m). The locations of the RSUs are depicted by the vertical dashed lines in all figures. The width of each lane is assumed to be 3 m. PHY and MAC layer parameters are configured according to the IEEE 802.11p protocol [28]. Table 1 summarizes the values of the used 802.11p parameters and the other simulation parameters. The RSU broadcasts periodic beacons containing the ID of the RSU, the location of the RSU, and the road geometry every 100 msec. To reduce the simulations time, we assume that the RSUs broadcast periodic beacons every one second without loss of generality. The mobility model of the vehicles is based on the modified random waypoint model [29]. According to the measurements presented in [24], two-way TOA ranging techniques are susceptible to

TABLE 1: Summary of simulation parameters.

Communication range of each RSU	500 m
Number of lanes per direction	3
Packet size	300 bytes
Bit rate	3 Mbps
Beacon broadcast rate	1 per sec
SIFS	32 μsec
AIFS	50 μsec
Slot time	9 μsec
(CW_{\min}, CW_{\max})	(15, 1023)

errors due to channel fluctuations, hardware, and other inaccuracies. Hence, we follow [24] and include the two-way TOA measurement noise modeled as an additive normal distribution with zero mean and 3 m standard deviation. The standard deviation of the different measurement noise components of the INS system is set to 0.5 m as reported in [12]. The parameters used in determining the lane-level vehicle location, α , M , and change-lane-threshold, CLT, were evaluated to be 0.1, 4, and 1.9, respectively, to get the best estimation of the lane-level vehicle location.

We use the root-mean-square error (RMSE) as our metric to evaluate the performance of our proposed framework. RMSE is defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (x_{\text{actual},i} - x_{\text{est},i})^2 + (y_{\text{actual},i} - y_{\text{est},i})^2}{n}}, \quad (28)$$

where $(x_{\text{actual},i}, y_{\text{actual},i})$ is the real vehicle location at time instant i , $(x_{\text{est},i}, y_{\text{est},i})$ is the estimated vehicle location at time instant i , and n is the number of time instants. The reported results are the average RMSE of 1000 simulation runs to get a stable estimate of the performance.

5.1. Impact of the Curvature Error. In order to investigate the curvature error ϵ_k inherited from the approximations assumed in (1), we first simulate the single RSU-based localization technique of the proposed framework given the curvature error as the only type of error. This allows us to determine the threshold regions within which the proposed ranging technique can/cannot be used to get the y -location of the vehicle. We consider a single vehicle moving at 20 m/s in the three lanes one at a time. Figure 7 shows that the localization error is negligible if the vehicle is away from the RSU and it increases as vehicles move towards the RSU. Hence, the claim that the curvature error is negligible compared to the error n_R in estimating the range between vehicles and RSU $R_{V,RSU}$ outside the threshold area is valid.

In order to determine the value of the threshold to be used, we simulate our proposed framework for vehicles moving at 20 m/sec in a road with 3 km length and take the average RMSE of 20 different mobility patterns. The simulation results showed that the best threshold in which we switch from using our ranging technique with Kalman filter to using extended Kalman filter for only INS data is 70 m

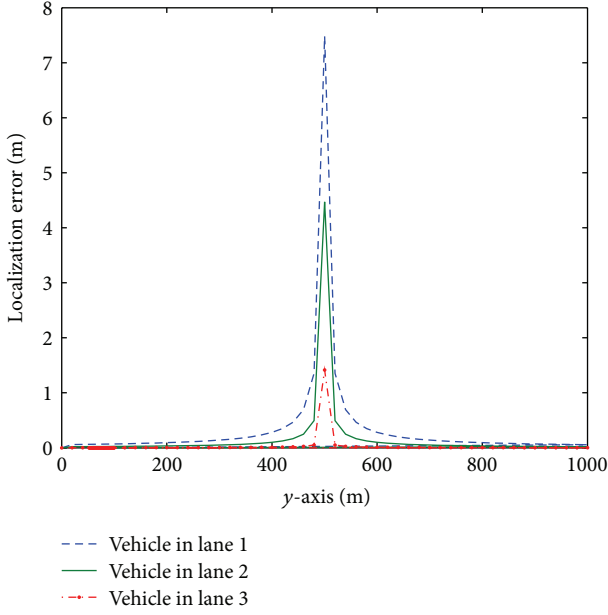


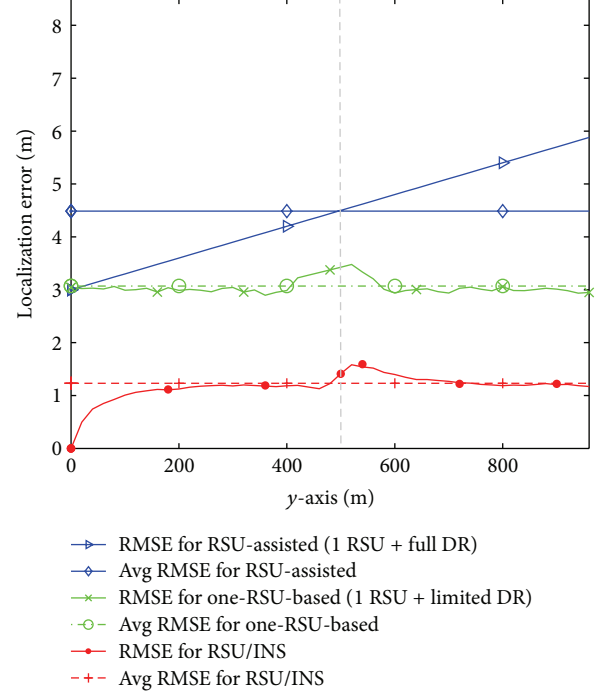
FIGURE 7: The impact of curvature error.

at each side of the RSU which corresponds to the minimum RMSE. This threshold value is used for the rest of the paper.

5.2. Localization Accuracy. As we discussed earlier in Section 2, some localization techniques only obtain the vehicle location along the road length (y -dimension), such as the one-RSU-based [9] and the RSU-assisted [8] localization techniques, and others obtain the vehicle location in both the x - and y -dimensions, such as GPS-standalone, faulty-free [7], and GPS/INS integration techniques. Hence, we divide our comparisons into two parts: one that evaluates the accuracy of the vehicle location in the y -dimension only and the other that evaluates the vehicle location in both x - and y -dimensions.

5.2.1. Localization Accuracy along the Road Length. Here, we evaluate the localization accuracy of \hat{y}_k obtained from our proposed RSU/INS integration. We simulate our proposed framework on a vehicle moving at 20 m/sec along the coverage area of only one RSU as shown in Figure 8. We assume that the standard deviation of the measurement noise n_r is $\sigma_r = 3$ m, which is consistent with the range measurement error which varies from 0.5 to 3.0 m [11]. We compare the y -location of our framework against the y -location obtained by other techniques such as the one-RSU-based [9] and the RSU-assisted localization [8] techniques.

Recall that the one-RSU-based localization technique only uses dead reckoning in a limited distance around the RSU while RSU-assisted localization uses dead reckoning, all the way after knowing the initial position, obtained from V2R communication and RSU's location. Hence, the localization error unboundedly increases with travel distance in the RSU-assisted localization technique [8] (which uses one RSU and

FIGURE 8: Accuracy of y -location \hat{y}_k of our framework.

uses full dead reckoning all the way). Meanwhile, the localization error of the one-RSU-based technique [9] (which uses one RSU and uses partial dead reckoning) increases when the vehicles move inside the threshold area around the RSU which is mainly due to the use of dead reckoning only inside the threshold area. On the other hand, the localization error of y -location \hat{y}_k obtained from our RSU/INS framework increases when the vehicles move inside the threshold area around the RSU which is mainly due to the use of extended Kalman filter inside the threshold area instead of Kalman filter. As we explained earlier, the linear relationship of the measurement equation is no longer valid inside the threshold area. However, the RMSE of the y -location \hat{y}_k of the proposed framework is only 1.2 meters, which is approximately 40% and 26.67% of the RMSE of the one-RSU-based localization and the RSU-assisted localization, respectively. Hence, the localization accuracy improvement of the y -location of the proposed framework is 60% and 73.3%, respectively.

5.2.2. Localization Accuracy along Both Road Dimensions. In order to estimate the localization accuracy of our proposed framework for the two-dimensions x and y of the vehicle location $\hat{\varphi}_k$, we simulate our proposed framework on a vehicle moving at 20 m/sec. Also, we compare our framework against techniques that provide a two-dimensional vehicle location such as the GPS-standalone, GPS/INS integration, and faulty-free [7] (which uses two RSUs, one on a different side of the road) techniques. We follow [11] in modeling the measurement noise of the GPS receiver via a Gaussian distribution with zero mean and 6 meters' standard deviation.

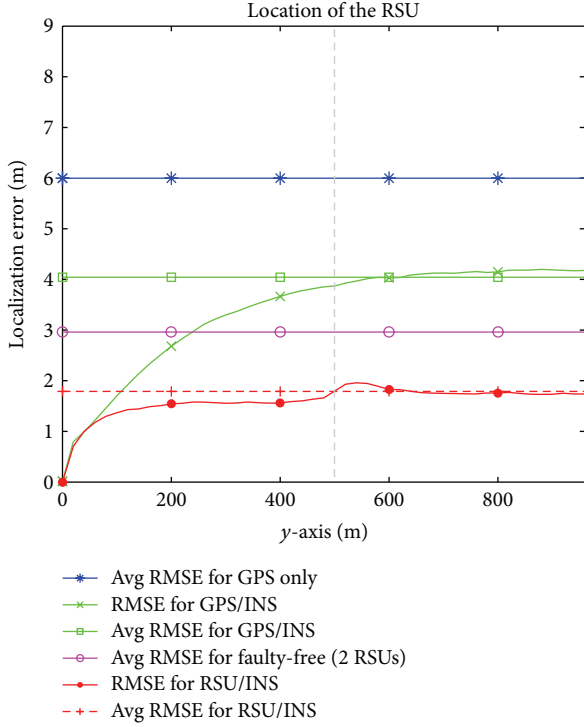


FIGURE 9: Accuracy of vehicle-location in both x - and y -dimensions.

As shown in Figure 9, the average RMSE of our proposed framework is 1.82 m compared to the average RMSE of GPS/INS localization and GPS-standalone technique which are 4 m and 6 m, respectively. Hence, our proposed framework improves the vehicle location by 54.5% and 69.67%, respectively. Figure 9 also shows that even though our approach uses only one RSU for localization, it provides better accuracy compared to the faulty-free localization technique which uses two RSUs. More specifically, our proposed RSU/INS framework improves the vehicle location by 39.33% compared to RMSE of the faulty-free localization technique.

It should be noted that the accuracy of the proposed framework depends on the regular deployment of the RSUs on one side of the road. If one RSU is temporarily not available, for example, due to failure, the vehicle will use only INS to update its location. In such a scenario, the achieved localization accuracy might be not robust enough to be used for collision avoidance applications but can be used by less sensitive applications such as routing, Internet access, and data dissemination protocols.

5.3. Impact of Measurement Errors. Next, we investigate the impact of the standard deviation of the range measurement error σ_r —which typically varies from 0.5 to 3.0 m [11]—on the localization accuracy of our proposed framework. We simulate our proposed framework on vehicles moving at various mobility patterns through 3 km road length and take the average RMSE for all mobility patterns. As shown in Figure 10, the average RMSE of \hat{y}_k decreases from 1.23 m

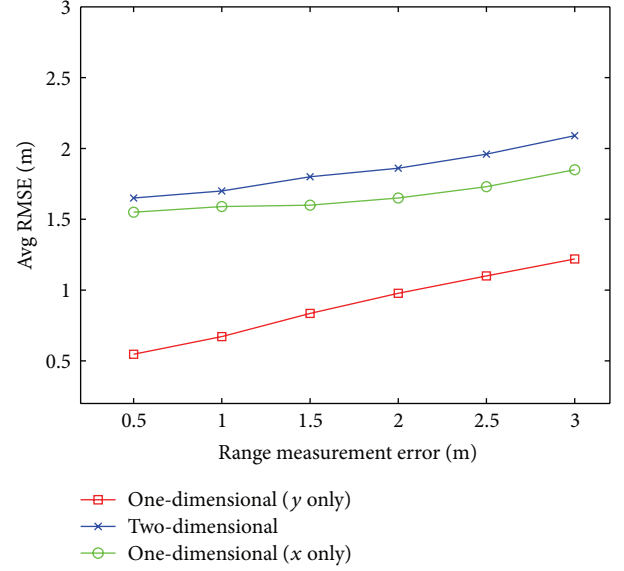


FIGURE 10: The impact of the range measurement error on \hat{y}_k , $\tilde{\phi}_k$, and \tilde{x}_k .

to 0.51 m as σ_r decreases from 3 to 0.5 m. Meanwhile, the average RMSE of two-dimensional vehicle location $\tilde{\phi}_k$ in both x - and y -dimensions decreases from 2.13 m to 1.68 m as σ_r decreases from 3 to 0.5 m. As shown in Figure 10, the accuracy of estimating the vehicle's y -location of the proposed framework is significantly better than estimating the vehicle's x -location because of the accumulation of error in the INS measurements. Recall that the proposed framework's *only* source of x -dimension data is through INS unlike the y -location that integrates the range estimate $R_{V,RSU}$ obtained in the second stage of the framework with the INS data.

5.4. Performance under Different Mobility Patterns. Here, we illustrate the performance of the proposed framework for different mobility patterns. First, we consider three vehicles moving on 3 km single carriageway with three-lane highway with three RSUs installed 1 km apart. Each vehicle stays in its lane for the entire road without changing lanes. One vehicle is traveling in the first lane ($x = 1.5$), the second vehicle is traveling in the second lane ($x = 4.5$), and the last vehicle is traveling in the third lane ($x = 7.5$). Figure 11 depicts the estimated trajectory taken by the average of \tilde{x}_k for x -dimension only. The localization error of x -location \tilde{x}_k for vehicles moving in the outer lanes slightly increases as the vehicle keeps traveling in the same lane due to the accumulation of INS error—unlike the middle lane for which the error is negligible. This is due to the fact that the road boundary constraint (used alongside the lane-level constraints) is symmetric for the middle lane while it is not symmetric for the outer lanes. Unlike the lane-level constraints, the road boundary constraint always pulls \tilde{x}_k towards the center of the road when estimation errors occur, regardless of which lane the car is traveling in. Next, we

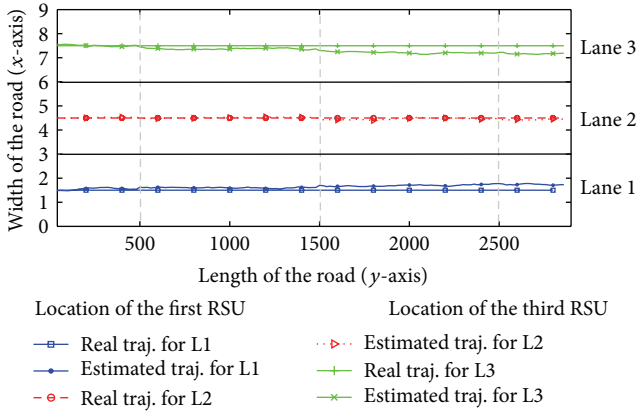


FIGURE 11: Real and estimated trajectories of the x -location for three vehicles moving in the first, second, and third lanes after applying the road and lane boundaries.

consider a more general mobility pattern in which the considered vehicle changes its lane frequently. Figure 12 shows the instantaneous performance of the proposed framework in this scenario. Figure 12(a) depicts the estimated trajectory of \tilde{x}_k alongside the real vehicle location. Our framework is capable of closely following the vehicle's real location. Figures 12(b) and 12(c) show that the localization error of our framework significantly outperforms all other techniques which only estimate the y -location (Figure 12(b)) or estimate the complete vehicle coordinates (Figure 12(c)). More specifically, the gain in reducing in the localization error of our approach is 60% and 73.3% compared to the one-RSU-based and RSU-assisted approaches, respectively. Likewise, the gain in reducing in the localization error of our approach is 65% and 47.5% compared to GPS and GPS/INS approaches, respectively. We considered different other random patterns and the gains of the proposed framework slightly vary around the reported result in Figure 12. We omit such results to avoid redundancies.

5.5. Impact of Traffic Density. Finally, we investigate the impact of changing the traffic density on our proposed framework. Unlike GPS-based techniques, which use messages transmitted from GPS-satellites, our proposed framework uses RTS/CTS handshake messages with RSUs to get the vehicles' locations. These RTS/CTS handshake messages cause time delay to get the vehicle location after receiving beacons from the RSU which is mostly caused by the random backoff mechanism. As the traffic density increases, more vehicles are to exchange RTS/CTS messages with the RSU, and, hence, more collisions are to be encountered. Consequently, the vehicles will wait more time before communicating with the RSU as the traffic density increases. We measure such an increase in the experienced localization delay for different traffic densities. As shown in Figure 13, the average delay increases almost linearly from 1.4 msec to 31 msec as the number of vehicles increases from 1 vehicle/lane/km to 20 vehicles/lane/km. As we mentioned earlier, RSUs broadcast beacons every 100 msec. Hence, all vehicles—even under high

density scenario—can update their locations with a maximum latency of 100 msec. This means that our framework does not only achieve high localization accuracy but also satisfies the latency requirement (less than 100 ms) in VANET DSRC safety messages.

6. Conclusions

In this paper, we have proposed a GPS-free vehicle localization framework that only relies on RSUs deployed only on one side of the road. Hence, our proposed framework decreases the required number of RSUs and hence the cost, compared to existing localization schemes which use multiple RSUs for vehicle localization. The proposed framework integrates the RSU-based localization information with the local inertial navigation system information via different Kalman filters to significantly improve the accuracy of vehicle localization. Our simulation results show that the accuracy of our GPS-free localization framework does not only significantly outperform the localization accuracy of GPS-based localization techniques but also outperform the existing GPS-free localization approaches—despite the use of a single RSU for localization. Consequently, our proposed GPS-free localization framework is most suitable for smart road applications that require high localization accuracy such as collision avoidance applications.

Notations

A, B :	Control metrics
C :	Speed of light
CLT :	Change-lane-threshold
EMA_K :	Exponential weighted moving average
ε_k :	Curvature noise which reflects the lane-level ambiguity
g_k :	Kalman gain used in one-dimensional Kalman filter
\underline{g}_k :	2×1 Kalman gain used in two-dimensional extended Kalman filter
$h(\cdot)$:	A nonlinear function used to compute the predicted single-value measurement, $R_{V,RSU}$
\underline{h}_k :	1×2 Jacobian vector of the partial derivatives of $h(\underline{q})$
L :	Length of the road
L_{RSU} :	y -coordinate of the RSU
L_i and L_{i-1} :	The boundaries of lane i
MA_K :	Moving average
M :	Number of prior observations of \tilde{x}_k
N :	North road driving direction
n_r :	Noise coming from range estimation, $R_{V,RSU}$
θ :	Angle between the y -axis and the vehicle motion direction
p_k :	A posteriori estimate error variance
\bar{p}_k :	A priori estimate error variance
P_k :	2×2 a posteriori estimate error covariance matrix

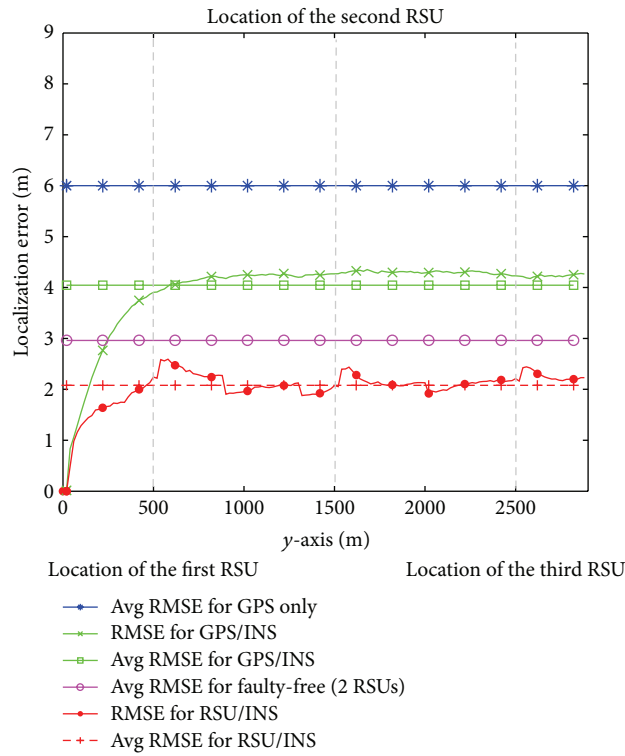
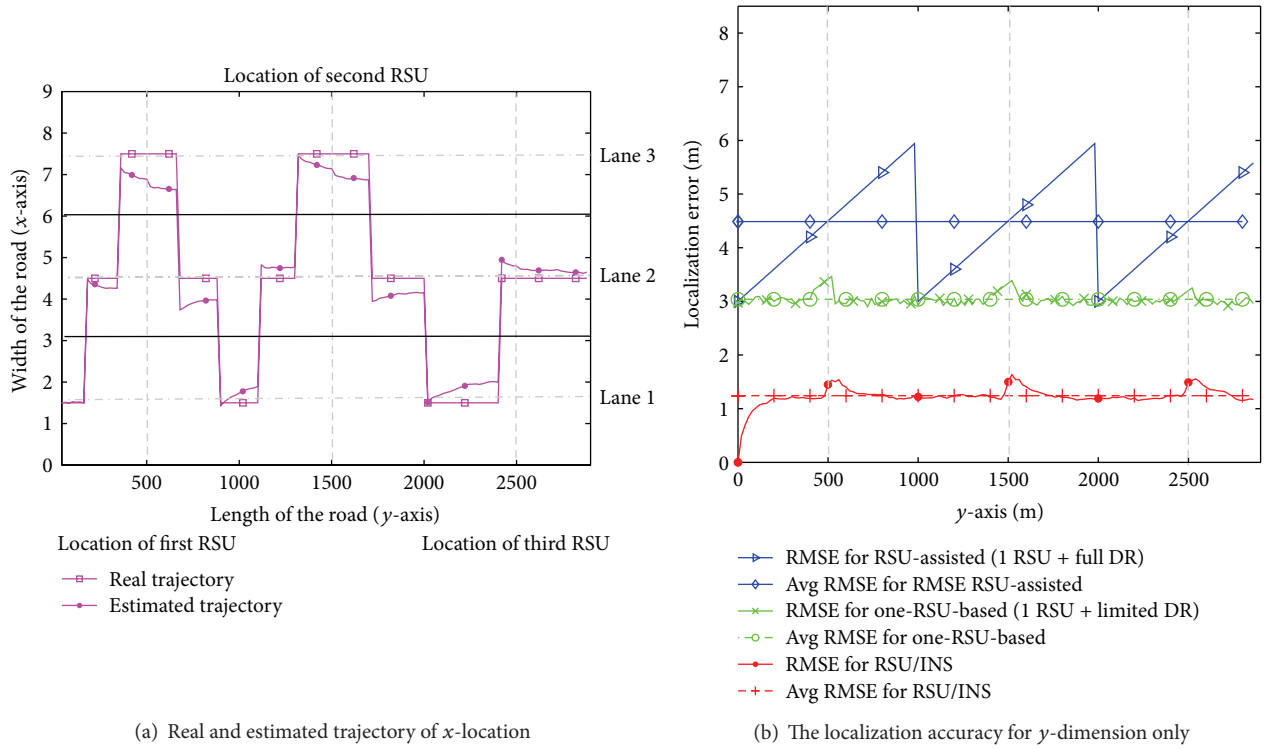


FIGURE 12: The vehicle localization accuracy of a vehicle moving in a random pattern.

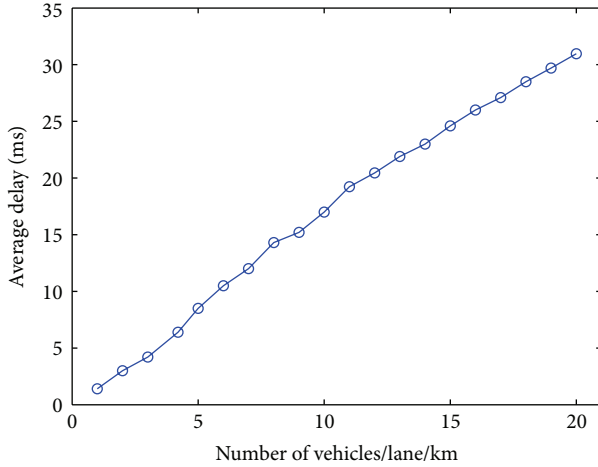


FIGURE 13: The impact of traffic density.

P_k^- :	2×2 a priori estimate error covariance matrix
Q :	2×2 covariance matrix of the process noise
$R_{V,RSU}$:	Estimated range between vehicle and RSU
S :	South road driving direction
T :	Time interval
τ :	Time delay experienced at the RSU
\underline{u}_k :	2×1 vector that represents vehicle velocity components in the x - and y -directions
v :	Vehicle speed
W :	Width of the road
w :	Process noise coming from using INS
\hat{y}_k :	Estimated vehicle location using our one-RSU-based approach at time t_k
\hat{y}_k :	A posteriori state estimate of the vehicle location in y -dimension
\hat{y}_k^- :	A priori state estimate of the vehicle location y -dimension
z_k :	Measurement
ζ_k :	Measurement noise
$\hat{\phi}_k^-$:	2×1 a priori state estimate of the vehicle location
$\hat{\phi}_k$:	2×1 a posteriori state estimate of the vehicle location.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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