Improving GPS-Based Vehicle Positioning for Intelligent Transportation Systems

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***Abstract*— Intelligent Transportation Systems (ITS) have emerged to utilize different technologies to enhance the performance and quality of transportation networks. Many applications of ITS need to have a highly accurate location information from the vehicles in a network. The Global Positioning System (GPS) is the most common and accessible technique for vehicle localization. However, conventional localization techniques which mostly rely on GPS technology are not able to provide reliable positioning accuracy in all situations. This paper presents an integrated localization algorithm that exploits all possible data from different resources including GPS, radio-frequency identification, vehicle-to-vehicle and vehicle-to-infrastructure communications, and dead reckoning. A localization algorithm is also introduced which only utilizes those resources that are most useful when several resources are available. A close-to-real-world scenario has been developed to evaluate the performance of the proposed algorithms under different situations. Simulation results show that using the proposed algorithms the vehicles can improve localization accuracy significantly in situations when GPS is weak.**

I. INTRODUCTION

The increasing need for mobility results in more traffic and congestion in cities, suburban areas, and even interstate highways. More vehicular traffic results in more accidents and emergency situations. Many think building new roads and repairing aging infrastructure are the best approaches for addressing these problems [1]. However, a brighter future for transportation can be obtained by using information technology within the transportation system and making it more intelligent. Intelligent Transportation Systems (ITS) exploiting different synergistic technologies have emerged to improve the safety and quality of transportation networks [1]. ITS have many applications from collision warning to law enforcement and environmental monitoring. Most applications of the ITS rely on accurate location information from the elements of the transportation network.

The most accessible vehicle navigation technique is the Global Positioning System (GPS). However, it is well-known that GPS cannot provide precise location information in all situations [2]. In other words, GPS receivers are unreliable in dense environments (e.g., urban canyons), indoor environments (e.g., parking garages, tunnels), or anywhere else without a direct view to sufficient number of satellites. However, several applications of ITS still require the location information of the elements in these places. Several techniques have been proposed to enhance the performance of GPS in such environments [3], [4].

Vehicular communications has been developed as a part of ITS which enables vehicles to broadcast their vital information to the neighboring nodes including infrastructure (Vehicle-to-Infrastructure or V2I), vehicles (Vehicle-to-Vehicle or V2V), and pedestrians (Vehicle-to-Pedestrian or V2P). To facilitate less interference communication, the United States Federal Communications Commission (FCC) has allocated 75 MHz of spectrum in the 5.9GHz band to vehicular communications which is referred to as Dedicated Short-Range Communications (DSRC). Vehicular communications can be employed not only for data exchange but also for positioning purposes. In particular, the infrastructure can play the role of GPS satellites [5]. Note that V2I communications refers to any form of communication between a vehicle and a static device with an exact known location (the so called anchor node). For instance, it can be done through a DSRC between the On-Board Equipment (OBE) installed in the vehicle and Roadside Equipment (RSE) installed at a traffic light [6], through cellular communications between the cellphone of the driver and the network base station [7], [8], or through a wireless sensor network operating in an unlicensed band [9], [10]. Similar to GPS, V2I communications can provide absolute vehicle locations. However, building infrastructure for this purpose can be expensive. Hence, V2V and V2P communications can be also used as alternatives [4], [11], [12]. Incorporating V2V and V2P in positioning is referred to as cooperative positioning where a vehicle communicates to other nearby nodes and uses their information to improve its location estimation [13]. It has been shown that using V2V ranging along with GPS can improve the positioning accuracy in comparison with standalone GPS techniques [14] and [15]. However, V2V and V2P communications can only provide relative positions of the vehicles and not their absolute ones. Therefore, V2V and V2P ranging would be beneficial only when vehicles have their approximate locations from a GPS receiver or a static device with an exact known location. In the case of a GPS outage, vehicles do not have their approximate locations and V2V and V2P communications cannot provide significant improvement.

Another technique to enhance the accuracy of GPS localization is map matching [4], [16], [17], where several databases including maps and information of the transportation network are incorporated in vehicle positioning. The processing time of location estimation using this method is

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typically high. Another disadvantage of these techniques is that GPS reception is required to have a reasonable accuracy, otherwise map matching would be useless.

Dead reckoning (DR) is another technique used to improve the positioning accuracy. In DR, previous information (location and velocity) is used to predict future information which helps the vehicle find its location more precisely [18], [19]. However, similar to V2V communications, DR techniques are useful only when GPS or a static device with exact known location are used to provide the approximate locations of the vehicle. The estimation error of DR techniques can be very large when DR is being used for a long period of time in case of GPS outage, as DR estimates the location of the vehicle merely based on prediction and previous estimates.

Several studies suggest incorporating radio-frequency identification (RFID) technology to improve the GPS accuracy [20], [21]. Although RFID results in more accurate localization, its performance relies heavily on GPS and would not be reliable in cases where GPS outages can happen. This technology can improve the positioning accuracy in places where GPS access is limited. However, stand-alone RFID cannot provide good accuracy indoors such as in parking garages and tunnels where GPS receivers do not operate at all.

In most of the studies mentioned above, an additional resource (V2I, V2V,V2P, RFID, and DR) to the standalone GPS is utilized to help the vehicle localize itself. Unlike previous studies, this study is not restricted to only one of the resources. An Integrated algorithm is proposed which enables the vehicle to use all different positioning techniques including GPS, RFID, V2I, and V2V. The proposed algorithm does not merely rely on any individual signal, but it can utilize them whenever any of them are available. For instance, unlike most previous studies in which the vehicle has to be connected to at least several GPS satellites, the proposed algorithm uses GPS satellites only when they are available and useful. A comprehensive evaluation and comparison is conducted to demonstrate the effectiveness of different positioning technologies for different environments.

We also studied the performance of the Integrated algorithm in dense environments, such as Downtown Manhattan in N.Y. In such environments, there are many vehicles present in the areas and they need to be localized at sufficiently high accuracy. Due to the large number of vehicles packed in a small area, the vehicles may have many connections with either infrastructure and/or other vehicles. The integrated algorithm uses all connections to estimate the vehicle's location. However, sometimes the vehicle has many connections and not all of them are necessarily useful. These connections slow down the estimation process and do not provide significant improvement. Therefore, an algorithm (the so called Smart algorithm) is proposed which only utilizes the most beneficial connections in estimating the vehicles' locations. The proposed Smart algorithm filters out the redundant connections and keeps only those connections that provide the desired accuracy. The proposed algorithms are developed and simulated in MATLAB. A transportation network scenario which includes several different situations is created and the performance of the proposed algorithms is evaluated through computer simulations.

II. Methodology

The main idea is to estimate the locations of the vehicles from a series of range measurements obtained from GPS satellites, V2I, V2V, and RFID connections. Moreover, the algorithm is able to use DR to improve the localization accuracy. Let $\mathbf{x}_i^k = [x_{v,i}^k, y_{v,i}^k, z_{v,i}^k]^{\mathrm{T}}$ be the location of the ith vehicle at the kth time-step and $\mathbf{y}_j^k = [x_{u,j}^k, y_{u,j}^k, z_{u,j}^k]$ be the location of jth unit at the kth time-step. Units refer to GPS satellites, anchor nodes, or RFID readers. There are N vehicles and M units in the network. Let $\mathcal{U}_i^k$ and $\mathcal{V}_i^k$ be sets of indices of the units (except RFID readers) and vehicles connected to the ith vehicle at kth time-step, respectively. Let r_{ij}^k be the range measurement between the ith vehicle and the jth unit (except RFID readers) at the kth time-step. Hence, it can be modeled as [2], [9]

$$\begin{aligned} r_{ij}^k &= d_{ij}^k + n_{ij}^k, \quad j \in \mathcal{U}_i^k \\ r_{il}^k &= d_{il}^k + n_{il}^k, \quad l \in \mathcal{V}_i^k \end{aligned} \tag{1}$$

where d_{ij}^k, d_{il}^k are the true distances, defined as:

$$d_{ij}^k = \sqrt{(x_{v,i}^k - x_{u,j}^k)^2 + (y_{v,i}^k - y_{u,j}^k)^2 + (z_{v,i}^k - z_{u,j}^k)^2}$$
$$d_{il}^k = \sqrt{(x_{v,i}^k - x_{v,l}^k)^2 + (y_{v,i}^k - y_{v,l}^k)^2 + (z_{v,i}^k - z_{v,l}^k)^2}$$

and n_{ij}^k, n_{il}^k define the measurement noises which are modeled as Gaussian random variables with variance σ_{ij}^2 [22]. Typically, the lack of perfect synchronization between the receiver and the GPS satellite [2] is considered by adding an extra parameter (clock offset) to (1). For the sake of simplicity, the effect of clock error is neglected here. However, it does not change the relative performance of the algorithms. The information obtained from an RFID reader cannot be modeled as (1). RFID measurements can be modeled as [23]:

$$d_{ij}^k \le r_{ij}^k, \quad j \in \mathcal{D}_i^k \tag{2}$$

where $\mathcal{D}_i^k$ is the set of indices of the RFID readers connected to the ith vehicle. r_{ij}^k for RFID readers are defined by their communication range. To consider DR, an underlying state model for the movement of the vehicles should be defined. Let $\mathbf{v}_i^k = [v_{x,i}^k, v_{y,i}^k, v_{z,i}^k]^{\mathrm{T}}$ be the velocity of the ith vehicle at the kth time-step. The relationship between the previous and current location of the vehicle can be modeled as [24], [25]:

$$\boldsymbol{\theta}_i^k = \mathbf{A}\boldsymbol{\theta}_i^{k-1} + \mathbf{w}_i^k \tag{3}$$

where $\boldsymbol{\theta}_i^k = [\mathbf{x}_i^k, \mathbf{v}_i^k]^{\mathrm{T}}$, and

$$\mathbf{A} = \begin{bmatrix} \mathbf{I}_3 & \Delta\mathbf{I}_3 \\ \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix}.$$

$\mathbf{w}_i^k$ defines the prediction error and is typically modeled as a Gaussian random variable with variance $\mathbf{Q}_{w,i}^k$. Δ is the time-step between two sets of measurements. $\mathbf{0}_3$ and $\mathbf{I}_3$ denote the 3×3 zero and identity matrices, respectively.

Now, the problem in hand is to estimate the location of the vehicles from noisy range measurements in (1), data from RFID readers in (2), and underlying state model in (3). A maximum a posteriori estimation (MAP) algorithm is used to estimate the locations of the vehicle from the range measurements and underlying state model [26], while data from RFID readers can act as a constraint on the estimation problem [11], [27]. Therefore, the location of ith vehicle at the kth time step is obtained from the following optimization problem [11]:

$$\begin{aligned}
\underset{\boldsymbol{\theta}_i^k}{\text{minimize}} \quad & \sum_{j\in\mathcal{U}_i^k} \sigma_{ij}^{-2}\left(r_{ij}^k - d_{ij}^k\right)^2 + \sum_{l\in\mathcal{V}_i^k} \sigma_{il}^{-2}\left(r_{il}^k - d_{il}^k\right)^2 \\
& + \left(\boldsymbol{\theta}_i^k - \hat{\boldsymbol{\theta}}_i^{k|k-1}\right)^{\mathrm{T}} \left(\mathbf{P}_i^{k|k-1}\right)^{-1} \left(\boldsymbol{\theta}_i^k - \hat{\boldsymbol{\theta}}_i^{k|k-1}\right) \\
\text{subject to} \quad & d_{ij}^k \le r_{ij}^k, \quad j \in \mathcal{D}_i^k \\
& \hat{\boldsymbol{\theta}}_i^{k|k-1} = \mathbf{A}\hat{\boldsymbol{\theta}}_i^{k-1|k-1}, \\
& \mathbf{P}_i^{k|k-1} = \mathbf{A}\mathbf{P}_i^{k-1|k-1}\mathbf{A}^{\mathrm{T}} + \mathbf{Q}_{w,i}^k \qquad (4)
\end{aligned}$$

where $\hat{\boldsymbol{\theta}}_i^{k-1|k-1}$ and $\mathbf{P}_i^{k-1|k-1}$ are the estimate and the variance of the location and velocity of the vehicle at the $(k-1)$th time-step, respectively. The estimate of the vehicle location and velocity at the current time-step is the solution of (4). The details for determining the variance of the estimate $\mathbf{P}_i^{k|k}$ can be found in [11]. In the problem in (4) the first, second, and third terms refer to vehicle-unit measurements, vehicle-vehicle measurements, and internal prediction, respectively. Moreover, the constraint in (4) refers to vehicle-RFID connection. The optimization problem in (4) does not have a closed-form solution. In the simulations, (4) is solved with the MATLAB routine *fmincon*. The problem in (4) can be solved in two ways: distributed and centralized [28]. In the former, the location of all vehicles is estimated simultaneously. In the latter, the location of each vehicle is estimated individually. Therefore in this case, the location of the desired vehicle is estimated by replacing the unknown locations of other vehicles with their predicted ones in (4). Although the centralized technique provides higher accuracy, its complexity grows exponentially as the number of vehicles increases. Hence, the distributed technique is employed here.

A. Smart Algorithm

Generally speaking, the more connections the vehicle has, the higher the accuracy of the localization will be. On the other hand, as the number of connections increases, the complexity of the algorithm intensifies. In the problem in (4), the vehicle is using all connections to estimate its location. However, sometimes the vehicle has many connections and not all of them are necessarily useful. These connections slow down the estimation process and do not provide significant improvement. This situation happens frequently in dense environments where a large number of vehicles are packed in a small area. In this case, a vehicle using V2V communications would have many connections to the other neighboring vehicles, most of them are not useful though. The Smart algorithm described here filters out the redundant connections and keeps only those connections that provide the desired accuracy. The proposed Smart algorithm processes the available connections and reports the useful ones to the Integrated algorithm in (4).

To evaluate whether a set of connections provide the desired accuracy or not the CramérRao lower bound (CRLB) is used. The CRLB expresses a lower bound on the variance of any unbiased estimator [26]. The CRLB is used as a benchmark to evaluate the performance of unbiased estimators. In other words, it tells us how accurate the estimator is and how far its performance is from the lower bound. The CRLB of the unknown variables to be estimated is obtained from diagonal elements of the inverse of the Fisher information matrix [26]:

$$\mathrm{CRLB}([\mathbf{x}_i^k]_m) = [\mathbf{I}(\mathbf{x}_i^k)^{-1}]_{mm}, \quad m = 1, 2, 3. \qquad (5)$$

The detail for calculating the Fisher information matrix (FIM) is provided in [11]. The CRLB of the location of the desired vehicle depends on the locations of the satellites, anchor nodes, and other vehicles connected to that vehicle and the variance of the measurements. Since the locations of other vehicles are unknown, the desired vehicle predicts their locations based on the state model to calculate the CRLB. The location of a vehicle consists of three variables (i.e., 3-D coordinates, x, y, and z) and the overall accuracy is calculated as $\sqrt{\mathrm{Trace}\{\mathbf{I}(\mathbf{x}_i^k)^{-1}\}}$ [9]. Since RFID connections do not provide range measurements, they cannot be included in the CRLB. Therefore, in this case, we assume that the vehicle only uses GPS, V2V, and V2I connections.

The proposed Smart algorithm is provided in Algorithm I. $\mathcal{A}_i^k = \mathcal{U}_i^k \cup \mathcal{V}_i^k$ is the set of all available connections at the kth time-step and $\mathcal{C}_i^k$ be the set of connections selected by the Smart algorithm ($\mathcal{C}_i^k \subseteq \mathcal{A}_i^k$). Suppose at the kth time step, $\mathcal{C}_i^{k-1}$ is available. In line 1, the algorithm calculates the intersection of the set of connections obtained from the Smart algorithm at the $k-1$th time step and the set of available connections at the kth time step. In line 2, the algorithm calculates the Fisher information matrix using the set $\hat{\mathcal{C}}_i^k$. In line 3, the difference between the desired accuracy, ϵ, and the predicted accuracy $\sqrt{\mathrm{Trace}\{\mathbf{I}^{-1}\}}$ is calculated. In line 4, If the predicted accuracy is better than required accuracy, $\delta < -0.15\epsilon$, the algorithm needs to remove a connection, because the Smart algorithm anticipates that the selected set $\hat{\mathcal{C}}_i^k$ can provide better accuracy than the desired one. However, the algorithm needs to determine which connection should be removed from the set. Intuitively, it is better to select the connection whose removal has the least impact on the predicted accuracy. One way to calculate the effect of removing or adding a connection on the predicted accuracy is to calculate the CRLB for the new set of connections from scratch. It typically takes a lot of processing time, especially when the number of connections is high. However, the Smart algorithm is only useful when the running time of the connection selection process plus location estimation based on those connections is less than that of the fully-Integrated algorithm using all connections. Therefore, instead

Algorithm I. Smart Localization Algorithm

1. $\hat{\mathcal{C}}_i^k \leftarrow \mathcal{C}_i^{k-1} \cap \mathcal{A}_i^k$
2. $\mathbf{I} \leftarrow \mathrm{Fisher}(\hat{\mathcal{C}}_i^k)$
3. $\delta \leftarrow \sqrt{\mathbf{I}^{-1}} - \epsilon$
4. **if** $\delta < -0.15\epsilon$ **then**
5. remove the worst connection, j, from the set, $\mathcal{C}_i^k = \hat{\mathcal{C}}_i^k - j$
6. **elseif** $\delta > 0.15\epsilon$ **then**
7. add the best connection, j, to the set, $\mathcal{C}_i^k = \hat{\mathcal{C}}_i^k \cup j$
8. **else**
9. do not change the set, $\mathcal{C}_i^k = \hat{\mathcal{C}}_i^k$
10. **end if**

of calculating the CRLB of the new set, the following approximation is used [29]:

$$(\mathbf{I} + \epsilon\mathbf{Z})^{-1} \approx \mathbf{I}^{-1} - \epsilon\mathbf{I}^{-1}\mathbf{Z}\mathbf{I}^{-1} \tag{6}$$

where $\mathbf{Z}$ is the FIM of the connection to be removed. Since matrix inversion is a complex process for large matrices, the impact of a new connection can be simply calculated by using above approximation ($\mathbf{I}^{-1}\mathbf{Z}\mathbf{I}^{-1}$) which can be determined significantly faster than calculating and inverting a new FIM. Therefore, adding or removing the considered connection changes the CRLB by $\mathbf{I}^{-1}\mathbf{Z}\mathbf{I}^{-1}$. In this case, the algorithm needs to remove a connection which has the least effect on the accuracy. Therefore, a connection which has the lowest value of $\mathrm{Trace}\{\mathbf{I}^{-1}\mathbf{Z}\mathbf{I}^{-1}\}$ is removed from the set.

In line 6, if the predicted accuracy is worse than the required accuracy, $\delta > 0.15\epsilon$, the algorithm needs to add a connection to the set to compensate the lack of sufficient accuracy. Similar to the previous case, selection of a connection is performed based on the CRLB. However, in this case, a connection which delivers the highest accuracy improvement should be selected. Again, the algorithm starts calculating $\mathbf{I}^{-1}\mathbf{Z}\mathbf{I}^{-1}$ for all available connections and selects the one that has the highest value of $\mathrm{Trace}\{\mathbf{I}^{-1}\mathbf{Z}\mathbf{I}^{-1}\}$. In line 8, if the predicted accuracy falls between $(0.85\epsilon, 1.15\epsilon)$, the algorithm proceeds without any changes. Note that a 15% tolerance is considered to prevent the algorithm from unnecessary processing. The user can change the tolerance depending on application requirements. Additional details about the proposed Smart algorithm can be found in [11].

The practicality of the proposed positioning system is dependent on two important components. First, a sufficient number of sensors or other resources should be installed along the roads to cover the areas that GPS fails. Although such resources are not available immediately, new technologies and advancements make it possible in near future. Second, since each positioning system works based on its own requirements and specifications (e.g., ranging technique, input and output information, and accuracy), a data fusion center is also required to make data homogeneous and send it to the algorithm.

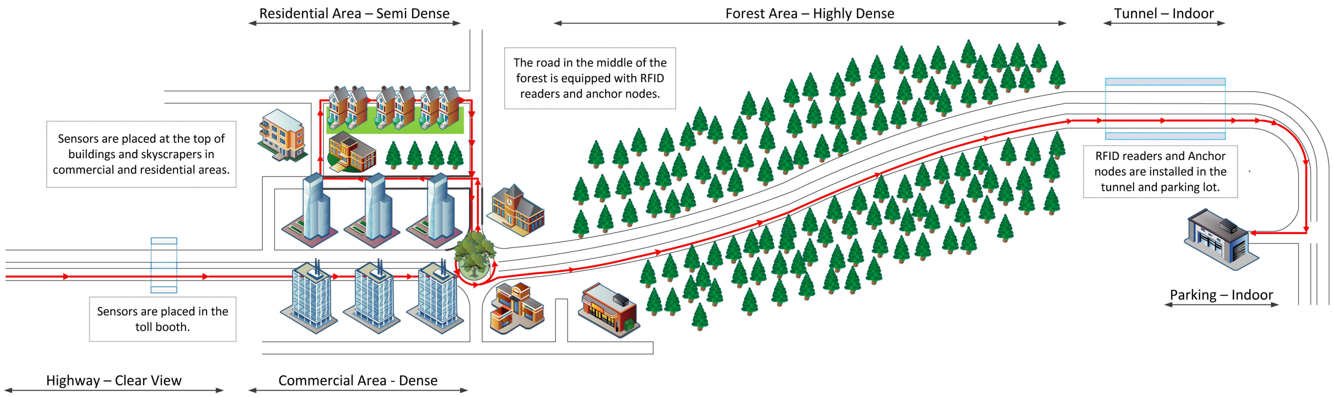
III. Simulation Results

In this section, the performance of the proposed algorithms is evaluated through computer simulations. The proposed transportation network and the traveling path of the desired vehicle are depicted in Fig. 1a. Different conditions are included in the simulated network. Several infrastructure and RFID readers are considered around the road. There are also 15 other vehicles in the network. The desired vehicle experiences five different environments through its travel. In the clear view areas, such as along a highway, there are no objects surrounding the road and the vehicle is connected to several GPS satellites. In the commercial areas, the road is surrounded by tall buildings and skyscrapers. The GPS reception in this area is weak. However, buildings are equipped with several anchor nodes and RFID readers which can help the vehicle find its location more accurately. The vehicle can also utilize V2V communications with surrounding vehicles. In residential areas, the condition is almost similar to the previous area, except GPS reception is more powerful in this area as the buildings are typically shorter. In the highly-dense areas, such as forest, the GPS reception is very weak. However, the road is equipped with several anchor nodes and RFID readers. In the indoor areas, such as tunnel and parking garage, no GPS reception is available.

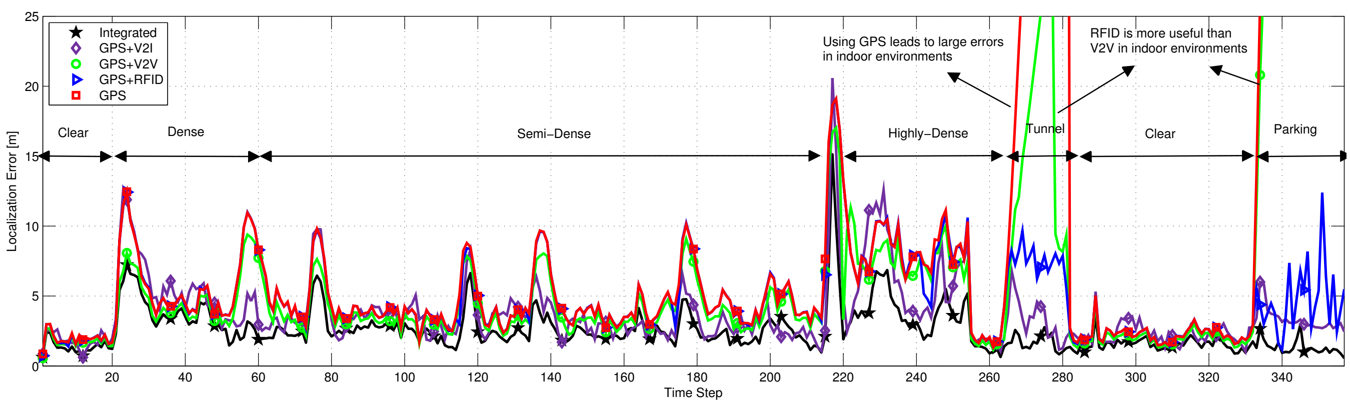
In the simulations, the true locations of the GPS satellites have been used. The Cartesian locations of the satellites are extracted from the ephemeris data using MATLAB script EASY17 [30]. The recent ephemeris information of the current 31 satellites is obtained from the National Geodetic Survey database. The reader is referred to [31] for more details about the simulation of the GPS satellites. The accuracy of the GPS range measurements is dependent on several parameters such as ionospheric effects, ephemeris errors, satellite clock errors, multipath distortion, and tropospheric effects [2]. As suggested in [31], experimental results show that the average error on the measurements of a GPS receiver depends on the elevation of the satellite and the environment where the receiver is located. The accuracy of the range measurement in V2I and V2P depends on the method of ranging [9]. In this work, time of arrival-based ranging method was considered whose accuracy depends on the received signal-to-noise ratio (SNR) and signal bandwidth [10]. SNR itself is dependent on the several parameters such as transmit power, environment, and receiver hardware. Another parameter that should be considered for V2I and V2V connections is the communication range. In TOA ranging, once SNR falls below a certain level, the signal cannot be detected by the receiver. The communication range is, in fact, the distance at which the signal power is so low that the receiver cannot detect it. No range measurement is performed among RFID components (readers and tags). Therefore, no measurement error is considered for RFID networks. However, the communication range of RFID readers would be different depending on the environment where they are located. The reader is referred to [11] for more details about simulation parameters.

A. Integrated Algorithm

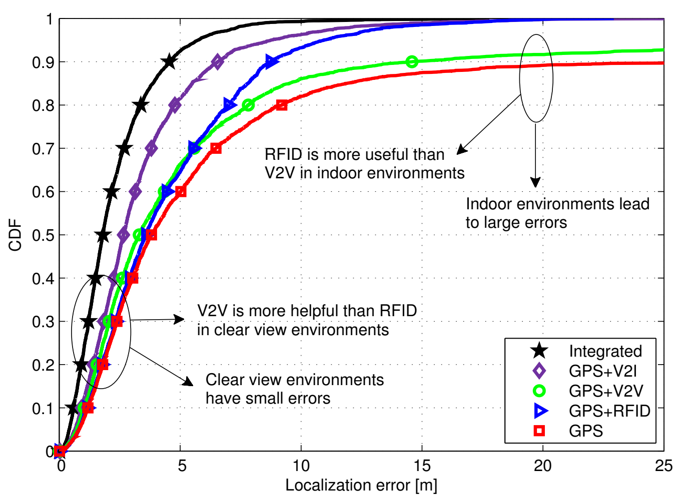
In this section, the performance of the Integrated algorithm is evaluated. Fig. 1 shows the simulation results of the Integrated algorithm. The localization error as a function of the time-step for these cases is depicted in Fig. 1b. Fig. 1c shows the cumulative distribution function (CDF) of the localization



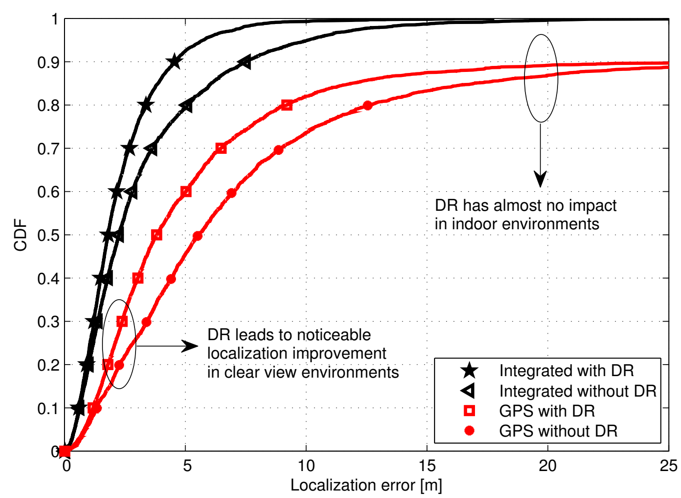
(a) The plot of the proposed transportation network.



(b) The localization error as a function of time-step.



(c) The CDF of the localization error.



(d) The CDF of the localization error with DR

Fig. 1. Simulation results of the Integrated algorithm.

TABLE I
THE POSITIONING PERFORMANCE OF THE CONSIDERED ALGORITHMS.

Algorithm	Integrated	GPS+V2I	GPS+RFID	GPS+V2V	GPS	Integrated w/o DR	GPS w/o DR
RMSE [m]	2.94	4.45	5.62	14.08	17.18	4.70	23.06
80% CDF [m]	3.37	4.78	6.99	7.82	9.20	5.08	12.55

error for different cases. The performance of GPS is almost satisfactory in all regions except for indoor (i.e., tunnel and parking) and very dense (i.e., forest) environments. On the other hand, the estimated location of the vehicle using the Integrated algorithm provides remarkable performance in all regions, especially in highly dense and indoor environments where GPS reception is very weak. The reason is that the integrated positioning exploits other resources which enhance the positioning accuracy. As depicted in the GPS+RFID curve, RFID technology can improve the location performance, especially when the vehicle is inside the tunnel and parking garage. However, in other regions where the GPS reception is sufficient, RFID technology cannot help the algorithm in terms of accuracy. The behavior of GPS+V2V is almost opposite to GPS+RFID. In other words, V2V technology can slightly help the vehicle in the clear view, commercial and residential regions because it provides the vehicle with more useful connections. However, V2V cannot improve the performance in indoor regions considerably, because in indoor environments V2V technology uses other vehicles information which are also inside the tunnel (or parking garage) and do not have enough connections due to GPS outage and their location information is not as reliable as other resources such as RFID and V2I. Among GPS-aided techniques (RFID, V2V, and V2I), V2I provides considerably better accuracy. The reason is that unlike RFID, V2I is associated with the range measurement which is more useful than presence detection for localization. V2I also has more valuable information than V2V because the source of information in V2I is an infrastructure with a fixed and known location, while the source of information in V2V is another vehicle whose location is not accurate.

In all previous cases, the algorithms use the internal DR. Evaluating the effect of the internal DR sensor, Fig. 1d shows that using DR is highly beneficial for both Integrated positioning and GPS positioning. However, DR is not useful for GPS positioning when the vehicle is in indoor environments. In DR technique, the previous estimate is used to predict the future vehicles locations. If no measurement is available and if the vehicle changes its velocity frequently, the prediction and the true location of the vehicle get farther and farther apart which generates significantly large errors. Therefore, using DR without having extra measurements does not necessarily lead to performance improvement. This conclusion is also clearly demonstrated in Fig. 1b where DR is not useful anymore when the vehicle enters the tunnel and parking garage, as DR predicts the wrong direction for the vehicle in the absence of measurements.

In Table I, the performance of the considered algorithms is summarized in terms of root-mean-square error (RMSE) and 80% CDF. RMSE represents the difference between the estimated location and the true one on average [11]. As can be seen, the RMSE of the GPS is about 17 m, although its localization error is less than 9.2 m about 80% of the time. The reason is that the bad performance of GPS which happens only 20% of the time has a great impact on the average error represented by RMSE.

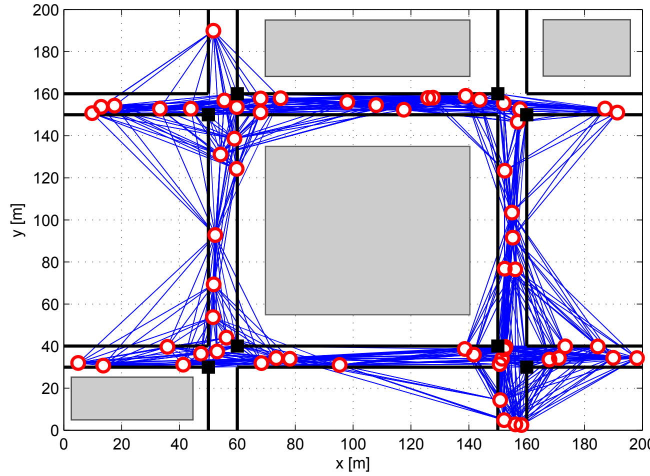


Fig. 2. The simulated network for the Smart algorithm.

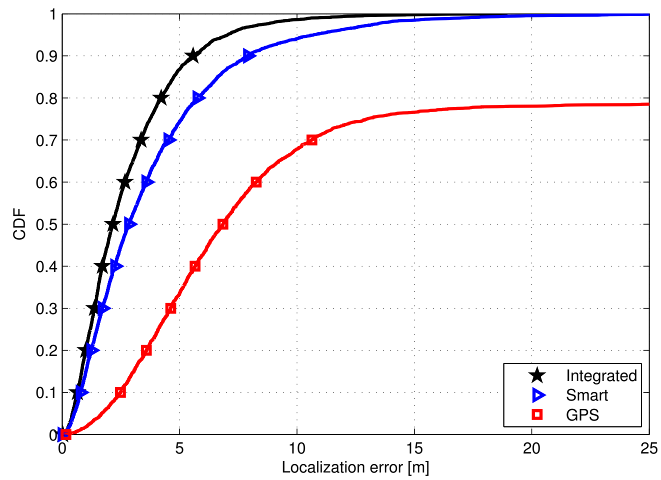


Fig. 3. The CDF of the localization error for the Smart algorithm.

B. Smart Algorithm

The performance of the proposed Smart algorithm is evaluated in this section. Fig. 2 features a network with 70 vehicles and 8 anchor nodes. The red circles and black squares represent the vehicles and infrastructure, respectively. Vehicles have access to GPS, V2V, and V2I connections. However, due to tall buildings and skyscrapers in the area, GPS reception is very week. The avarage number of satellites connected to the each vehicle is limited to 6 which is typical in dense environments. The satellites are selected randomly and based on their elevations [31]. The accuracy, ϵ, is set to 7m for the Smart algorithm.

Fig. 3 shows the CDF of the localization error for the Smart algorithm. The performance of standalone GPS is not satisfactory, mainly because of tall buildings blocking the line-of-sight view of the satellites. About 20% of the time, GPS fails to operate, as vehicles are not connected to a sufficient number of satellites. The Integrated algorithm performs significantly better than GPS, since vehicles have access to the other resources including V2V and V2I. However, the Integrated algorithm requires higher computations than the GPS. The average number of connections for the Integrated algorithm and GPS are 25 and 6, respectively. The Smart algorithm performs almost as good as the Integrated algorithm and significantly better than standalone GPS. However, the average number of connections for the Smart algorithm is only 5. The computational complexity of the optimization problem in (4) is difficult to determine due to its nonlinear behavior. It has been shown in [32] that the complexity of such problems is proportional to $O(m^3)$, where m is the number of measurements. Therefore, the complexity of the Smart algorithm is expected to be $(5/25)^3 = 0.8\%$ of that of the Integrated algorithm. As can be seen, the Smart algorithm is able to decrease the complexity significantly without affecting the performance.

IV. Conclusions

In this paper, Integrated and Smart positioning algorithms were proposed for ITS. Location information plays an important role in many ITS applications. The locations of vehicles in a network needs to be available under any atmospheric and geographic environment. Conventional vehicle positioning technologies mostly rely on GPS which does not work properly in all conditions. Taking advantage of multiple technologies such as V2I, V2V, RFID, and DR, an Integrated algorithm was proposed. A close-to-real-world scenario was developed and simulated to evaluate the performance of the proposed algorithm under different conditions. For the Integrated algorithm scenario, GPS failed to provide reasonable accuracy in about 15% of the situations, especially when the vehicle was in indoors (e.g., parking garages) or in highly-dense areas. The proposed fully Integrated algorithm provided significantly better performance in indoor areas and more than 50% improvement in other areas. Among considered technologies (V2I, V2V, and RFID) incorporated with GPS, V2I was most helpful. Comparing GPS+V2V and GPS+RFID positioning, the former and the latter add more improvement to stand-alone GPS accuracy in clear and indoor environments, respectively. In addition, a Smart algorithm was introduced to wisely choose useful links yet provide the desired accuracy in dense areas. The Smart algorithm was able to perform nearly as good as the Integrated algorithm with considerably lower complexity.

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