Computer Simulations of the Vehicle Localization for Intelligent Transportation Systems

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ABSTRACT

In this paper, an integrated framework and a smart algorithm for vehicle positioning are proposed. The standalone Global Positioning System (GPS) cannot provide accurate location information in dense and indoor environments. Therefore, an integrated framework is proposed which exploits additional positioning technologies including vehicle-to-infrastructure and vehicle-to-vehicle communications, radio-frequency identification, map matching, and dead reckoning for vehicle localization. Since different applications require different location accuracy, a smart algorithm is also provided which shows how different localization technologies under various situations are selected and used to obtain the desired accuracy with the least amount of complexity. A series of comprehensive MATLAB simulations are conducted to evaluate the performance of the algorithms. Simulation results show that standalone GPS is not a reliable positioning technique in all situations; second, an integrated technique using several positioning technologies is required to achieve the minimum application requirements in all situations; third, using the smart algorithm, the required accuracy and latency can be achieved by selectively adding or removing localization resources.

INTRODUCTION AND RELATED WORK

The significant growth of population and vehicles demands more reliable and efficient transportation networks everywhere, from large and small cities to suburb and rural areas. Intelligent Transportation Systems (ITS) have emerged to improve safety, efficiency, and navigation quality of the transportation networks by taking advantage of different technologies (Boukerche et al. 2008).

Current vehicle positioning techniques highly rely on GPS. However, GPS cannot provide reliable location information for all applications in all situations. GPS does not work at all in indoor environments such as parking garages and tunnels due to severe attenuation of satellite signals and its performance suffers severely from multipath in dense environments such as forests and commercial areas (Hofmann-Wellenhof et al. 1997; Vaghefi and Buehrer 2013). Therefore, there is a need for an alternative positioning technique which is able to provide the localization accuracy requirements of all ITS applications under different geographical areas.

Another major challenge in this field is that each application of ITS requires a specific localization accuracy at a specific latency. For example, collision warning is a safety application which requires highly accurate location information at the least amount of latency (Shladover and Tan 2006). In this paper, an integrated framework and a smart algorithm are proposed to address these two challenges. The reader is referred to (Amini 2013) for more details about different ITS application accuracy and latency requirements.

INTEGRATED FRAMEWORK

An integrated positioning framework to enhance the performance of GPS technology is introduced. In this framework, the vehicle is able to exploit all positioning technologies available and does not exclusively rely on GPS connections. In the proposed framework, besides GPS, other techniques including vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications, radio-frequency identification (RFID), map matching (MM), and dead reckoning (DR) are used. Although several similar approaches have been suggested previously in the literature (Bevly and Farrell 2013; Boukerche et al. 2008; Parker and Valaee 2006), no computer simulations or real-world experiences are performed to validate their approaches. In this paper, a closed-to-real scenario is developed in MATLAB and the performance of the proposed integrated framework is evaluated. The advantages and disadvantages of each localization technology are also discussed in detail.

GPS is a satellite-based navigation system which is widely used for vehicle localization. A GPS receiver collects a series of time-of-arrival (TOA) measurements from several satellites with known locations and uses them to determine its location. In order to find the vehicle location, the GPS receiver needs to connect to at least four satellites (Hofmann-Wellenhof et al. 1997). However, in some situations, the receiver is not able to communicate with enough satellites. Sensor and cellular localization can alternatively be used in these situations (Patwari et al. 2005; Vaghefi and Buehrer 2014). In this case, a base station (BS) or an anchor node (AN) plays the role of a satellite. TOA measurements between the vehicle and BS (or AN) can be used to find the vehicle location. BSs and ANs are fixed and their locations are known. Therefore, in this context, the connection between the vehicle and BS (or AN) is referred to as V2I communications. Besides communication with infrastructure (BS or AN), the vehicle is also able to communicate with neighboring vehicles and collects TOA measurements from them. This type of connection is referred to as V2V communications (Yao et al. 2011). RFID is a wireless technology which uses radio-frequency electromagnetic fields to transfer data from a RFID tag to a RFID reader. RFID can be used for both localization and data transfer simultaneously (Ali and Hassanein 2009). However, unlike GPS, V2V, and V2I, RFID readers are not able to measure ranges from RFID tags. In fact, a reader is only able to tell whether or not a specific tag is inside its communication range. In a MM technique, data and information from roads and maps are incorporated to enhance the accuracy of localization (Jagadeesh et al. 2004). Last but not least, in DR technique, the previous vehicle locations are used to increase the accuracy of future estimates. An underlying dynamic model is used to predict the next location of the vehicle which is then combined with the measurements obtained from other resources such as GPS to estimate the vehicle location and to provide a more accurate estimate (Aono et al. 1998).

Many studies have considered different localization techniques in which an auxiliary resource is used to assist GPS to provide better accuracy such as GPS+V2V (Yao et al. 2011), GPS+RFID (Lee et al. 2012), GPS+MM (Kim 1996) and GPS+DR (Aono et al. 1998; Farrell 2008). However, these techniques fail to operate properly when GPS does not work at all, since the assisted techniques are not able to localize the vehicle in the absence of GPS reception. In the proposed framework, the system is not limited to GPS connections and uses them only if there are available.

In order to exploit the proposed integrated framework, a localization algorithm is required which is able to utilize all resources mentioned above. Since each of these resources has their own specific characteristics, such as synchronization, measurement type, communication range, etc., the algorithm should be able to take all the aspects and requirements into account. The derivation of such algorithm is outside scope of this paper. However, the reader is referred to (Amini 2013) for the details of such algorithm.

SMART ALGORITHM

Different ITS applications need different localization accuracy and latency requirements. Therefore, a smart algorithm is proposed which regulates the number of resources used for localization in order to achieve the desired accuracy at the least latency. In the previous section, we proposed an integrated technique in which several resources are used to localize the vehicle. However, sometimes the vehicle is connected to several units and not all of them are necessarily useful. These connections slow down the estimation process and do not provide significant improvement. The smart algorithm proposed here filters out the redundant connections and keeps those connections that provide the desired accuracy. Therefore, the proposed smart algorithm processes all available connections and reports only the useful ones to the integrated algorithm.

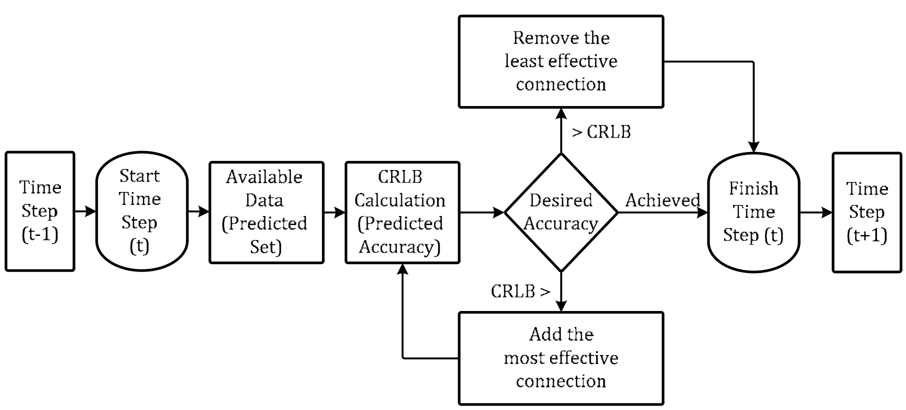


Figure 1. Flowchart of the smart algorithm.

Figure 1 shows the flowchart of the proposed smart algorithm. In each time step, the set of links from the previous step is provided to the algorithm. Then the algorithm checks how many of those links are still connected (this set is called predicted set). It also collects all other links available to the estimator. Then, the algorithm calculates the Cramér–Rao lower bound (CRLB) of the predicted set. The CRLB expresses a lower bound on the performance of any unbiased estimator (Kay 1998). Therefore, CRLB is used here to predict the performance of the predicted set (called predicted accuracy). Then the algorithm compares the predicted accuracy with the desired accuracy (which is determined by the application). If the desired accuracy is achieved the algorithm continues without changing the predicted set. If the desired accuracy is larger than the predicted accuracy, the algorithm has more than enough connections. In this case, the least effective connection (only one connection) is removed from the set. On the other hand, if the desired accuracy is smaller than the predicted one, the algorithm does not have enough connections; therefore, the most effective connection is added to set. In this case, the process is repeated until the desired accuracy is achieved. The selection of links to be removed or added is processed based on the CRLB. The detail for the selection process is provided in (Amini 2013).

SIMULATION RESULTS

In this section, the performance of the proposed algorithms is evaluated through computer simulations. The steps taken to simulate the algorithm performance are depicted in Figure 2. Frist, the network is designed and the locations of elements are defined. Then, the true ranges between the elements are calculated. The links between the elements are determined based on different types of environments (e.g., clear view, dense, and indoor environments) and other related parameters. The measurements are simulated by adding noise (typically Gaussian random variables) to the true values. Then, the algorithm uses the simulated measurements to estimate the locations of the vehicles. Finally, the estimation error is obtained by comparing the estimated locations with the true ones. Simulation parameters are selected based on previous real world studies and experiments. The reader is referred to (Amini 2013) for more details about simulation parameters.

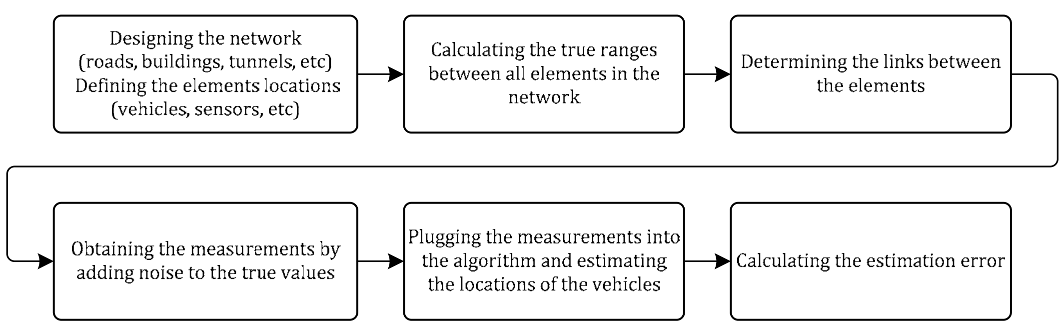
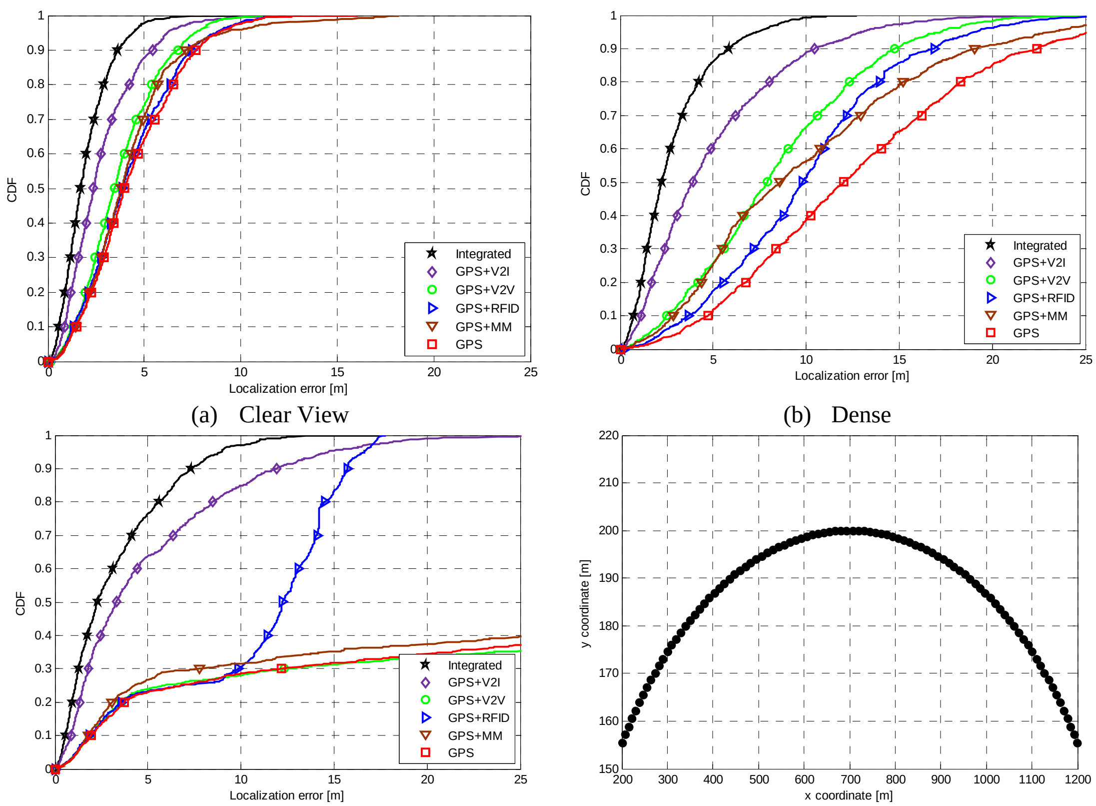


Figure 2. Simulation steps.

Localization Techniques Comparisons. In this simulation, different vehicle localization techniques are compared under four geographical environments: clear view, semi-dense, dense, and indoor. In clear view environments such as highways and rural roads, the vehicle has access to sufficient satellites and the effects of multipath and shadowing are not significant. In dense environments such as downtown of large cities and forest areas, the vehicle typically has limited access to GPS satellites and the signals from satellites are highly affected by severe multipath and attenuation. In indoor environments such as tunnels and parking garages, the vehicle does not have any connection to GPS satellites, as the signals attenuate sharply and are not received by the GPS receiver.



(a) Clear View (b) Dense

(c) Indoor (d) Simulated road

Figure 3. Simulation of different localization techniques.

Figure 3 shows the performance of different vehicle localization techniques along with the integrated algorithm in different environments. In

Figure 3d, the road used for the simulation is depicted. In each scenario, the vehicle travels the same path but the environment is changed. Note that DR is incorporated in all algorithms. In the clear view environment (

Figure 3a), all algorithms perform similarly. There are several GPS connections with high resolution, and adding more resources does not improve the accuracy significantly. The integrated algorithm outperforms other algorithms, as it has access to more resources. V2I provides more improvement to the stand-alone GPS than any other techniques. In the dense environment (

Figure 3b), the stand-alone GPS has the worst performance, since GPS connections are limited and have low resolution due to multipath and shadowing. V2V, map matching, and RFID assist GPS to have better accuracy. GPS+V2V perform better than the other two assisted techniques. V2V provides more ranging measurements, while RFID only detects the presence of the vehicle and map matching can only keep the estimate of the vehicle location inside the roads. Therefore, V2V actually provides more valuable information than the other two techniques. Similar to the previous cases, V2I adds more improvement to GPS, since first it provides more ranging measurements and second it is originated from fixed infrastructures (BS or AN) with exact known locations. In the indoor environment (

Figure 3c), the stand-alone GPS completely fails to provide reasonable accuracy. Moreover, map matching and V2V cannot improve the accuracy of GPS in this case because their performances highly rely on GPS. The ranging measurements obtained from V2V connections are not useful, as other vehicles do not have their own accurate locations. Therefore, they cannot operate efficiently when GPS does not work at all. RFID is more useful than the other two techniques, since its performance does not completely rely on GPS. The good performance of the integrated algorithm is achieved mainly from V2I connections.

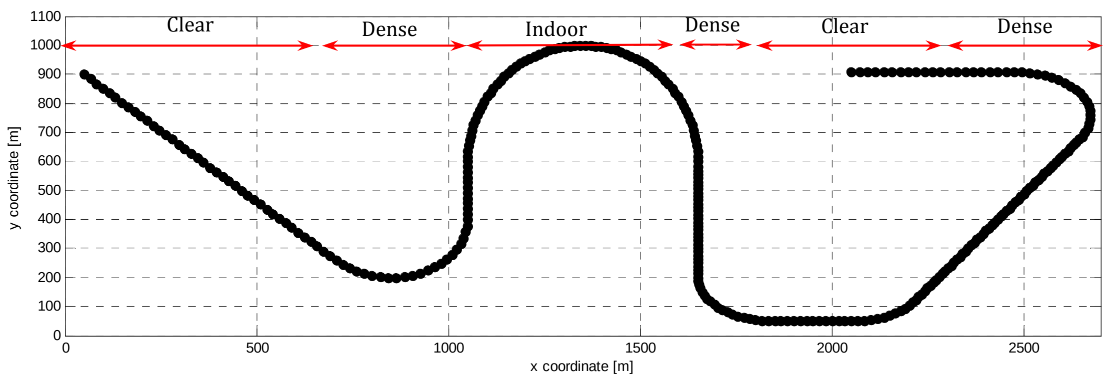


Figure 4. The simulated road for the smart algorithm.

Performance Evaluation of the Smart Algorithm. To evaluate the performance of the proposed smart algorithm, a close-to-real scenario is created in MATLAB. The scenario includes several geographical environments, a desired vehicle traveling a path of 314 time steps, 11 other vehicles, and a series of RFID and infrastructure distributed in network. During the travel time of the vehicle, the required accuracy is changed over time: 1-100, 101-200, and 201-314 time steps are set to low (12m), medium (7m), and high (3m) localization accuracy, respectively. Therefore, the desired vehicle experiences different environments and different localization accuracies during its travel. Figure 4 shows the road used to simulate the smart algorithm.

Figure 5 shows the comparison between the localization error of the fully integrated algorithm, stand-alone GPS, and smart algorithm. Different environments are indicated on the figure. At the beginning, the accuracy is set to low for the smart algorithm; hence, it is decreasing the number of connections one at a time until the desired accuracy is achieved. Note than at the time step 74, the vehicle enters an indoor environment where there is no GPS connection. In this case, the smart algorithm has few connections to select and needs to use all of them. Then the vehicle goes to a clear view environment and has access to many connections. Now, the smart algorithm can regulate the connection based on the desired accuracy which in this case is set to medium. After time step 201, the desired accuracy is set to high and the smart algorithm needs to use most of the connections. In this case, the algorithm rapidly adds all the required connections in one time step to achieve the desired accuracy. As can be seen, the smart algorithm delivers the desired accuracy by using the fewest possible connections. The running times of the smart algorithm for the three accuracy regions of low, medium, and high are 58%, 66%, and 99% of those of the fully integrated algorithm, respectively. As depicted in Figure 5, GPS generates large errors in indoor and dense environments.

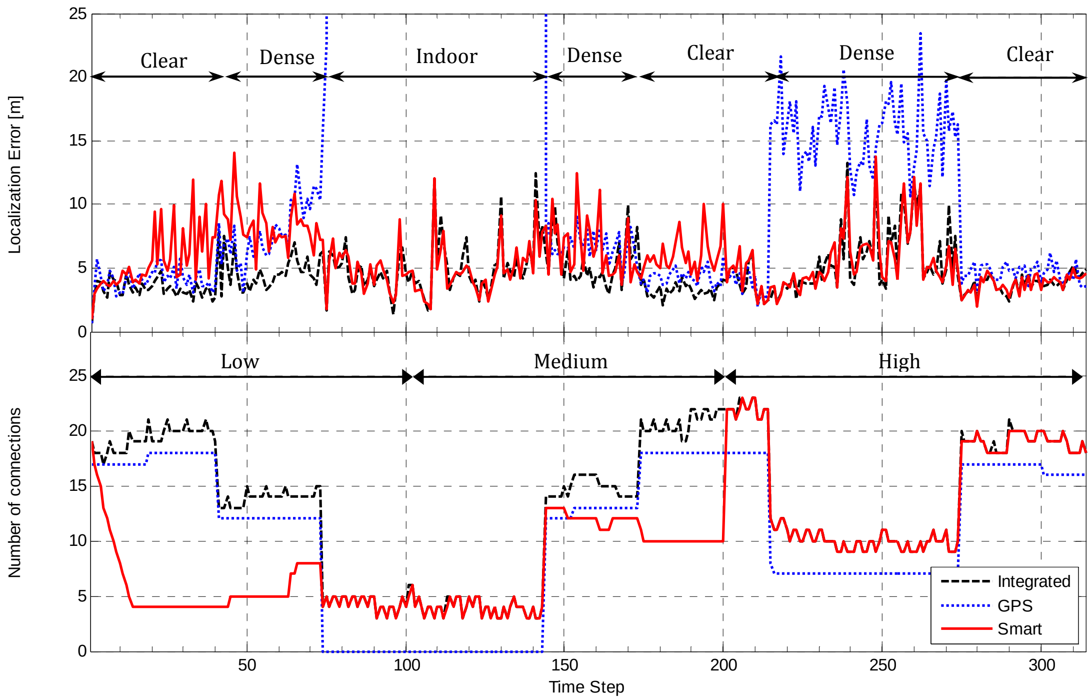


Figure 5. Simulation of the smart algorithm.

CONCLUSION

In this paper, two open challenges in the field of vehicle localization were addressed. First, the locations of vehicles are required everywhere in a transportation network. Since GPS is not able to achieve this goal, an integrated framework which takes advantage of several positioning techniques was introduced. Computer simulations were performed to show the advantages and disadvantages of each technique in different geographical environments. More specifically, it was shown that V2I communications can improve the localization accuracy more than other techniques. V2V communications and map matching are more useful in clear and dense environments than in indoor environments. The integrated algorithm outperforms other algorithms in all situations. Second, different localization accuracies are required based on application. A smart algorithm was introduced to regulate the number of connections based on the desired accuracy and provide the location of the vehicle at the least amount of latency. Computer simulations showed the effectiveness of the proposed smart algorithm.

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