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Two Stage Integration of GPS, Kinematic Information, and Cooperative Awareness Messages Using Cascaded Kalman Filters

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Abstract. Availability of accurate and continuous positioning information is a fundamental requirement for Vehicular Ad Hoc Networks. However, existing positioning approaches does not fulfill the required accuracy of many VANET's applications and services. Integrating GPS with vehicles' kinematic information (GPS/DR) is widely suggested for vehicular positioning. In many cases where the GPS is unavailable or instable for long time, this integration resulted in inaccurate positioning. Recently, cooperative positioning (CP) based on vehicle-to-vehicle (V2V) communication have been proposed as an alternative for GPS/DR in many ad hoc networks. Even though, CP needs high communication to achieve the required accuracy, which is not guaranteed in VANET harsh environment. In this paper, two-stage integration algorithm is proposed to ensure continuous and accurate positioning information. The proposed algorithm integrates GPS and kinematic sensors measurements, as well as neighboring mobility information based on two cascaded Kalman filters (KF). The first KF is used to integrate GPS information with kinematic sensors measurements (dead reckoning). Meanwhile, the second KF is used to integrate the results of the first KF with the neighboring mobility information. Results show that the proposed algorithm outperformed the conventional integration algorithm in terms of positioning accuracy under the tested scenario.

Keywords: GPS · Mobility information · Cooperative awareness messages · Kalman filter · Multilateration

1 Introduction

Recently, road crashes are increasing and it is expected to be the fifth leading cause of death in 2030 [1]. According to WHO [2], traffic accidents are annually killing 1.3 million people. In addition, traffic congestions impose a considerable cost to society such as losing billions of dollars for treatment of injured, cost of lost properties, and lost

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working hours due to delays, and cost of consumed fuel [2, 3]. Intelligent Transportation System (ITS) and Vehicular Ad Hoc Network (VANET) are proposed mainly for improving passenger's safety and traffic efficiency. VANET is the main component of future ITS. In VANET, vehicles have the capability to communicate with each other (V2V), with the nearby roadside units (V2R) or with infrastructure (V2I). Position information is crucial information for most VANET applications [4]. Most of VANET applications need high accuracy and availability of the poisoning information. Accurate positions' information is vital for their performance [5–7]. However, due to the harsh environment, acquiring accurate positioning information is a major challenge in VANET [5–7].

Vehicle positioning has been the topic of active research in the past years. Global Navigation Satellite Systems (GNSS) such as the Global Positioning System (GPS) are communally used for vehicles positioning. It is suggested for many applications due to its pervasive, simple and low cost. However, it is not effective for VANET emerging applications due to their limited accuracy and availability. GPS is vulnerable to noise, weather condition, and obstacles. For example, it is difficult to obtain accurate positioning in a tunnel or under an overpass, as well as between high buildings such as skyscrapers. Many solutions have been proposed for improving GPS accuracy through additional infrastructures such as Deferential GPS units (DGPS), and road side units (RSU). However, these solutions need intensive infrastructure and maintenance plans.

Another attempt to improve positioning accuracy is to integrate GPS with other source of information such as kinematic sensors (inertial navigation) and geoformation such as digital map. GPS and dead reckoning complement each other's drawbacks [8]. The dead reckoning improves the positioning information during GPS outages, while the GPS corrects dead reckoning drift. However, when GPS positioning information is corrupted or GPS is unavailable for long period of time, dead reckoning brings significant error due to the drift of the inertial sensors [9]. Similarly, GPS should be stable in order to correct dead reckoning drift. Unfortunately, there are many roads surrounded by obstacles in which GPS is affected by multipath delay and outages such as urban environment, canyon, and under the bridges to mention a few. Thus, both GPS and dead reckoning alone cannot provide long time stability which results in large error due to inaccurate integration.

Recently, many innovative positioning approaches were presented for improving positioning accuracy in vehicular networks based on cooperation between communicating vehicles. Approaches such as using cooperative positioning (CP) [1], dynamic DGPS (DDGPS, or Mobile DGPS) [10] and cooperative map matching (CMM) [11] exploit the vehicular communication to enhance the positioning accuracy. Unfortunately, VANET is a highly dynamic network in which the communication link among vehicles is shortly lived and frequently disconnected. This causes loss of positioning information and affect the continuity of acquiring position information of the neighboring vehicles. Therefore, obtaining accurate positioning is still an open problem in VANETs.

In this paper, two-stage integration algorithm is presented for improving vehicle positioning based on Kalman filter (GPS/DR/V2V). Kalman filter is selected because it is efficient for real time applications. In addition, Kalman filter includes the uncertainties of the fused information into account to enhance the estimation accuracy. Three positioning sources are integrated together in order to complement each other's weaknesses. GPS, dead reckoning, and cooperative positioning are integrated into two stages. In the first stage, GPS is integrated with dead reckoning (GPS/DR) so that later it can compensate GPS blockage time. Then, based on the certainty of first integration, multilateration (MLAT) method in [12] based on cooperative positioning namely (GPS/DR/V2V) is used in the second stage to further enhance the positioning information.

The rest of the paper is organized as follows. The proposed algorithm is elaborated in Sect. 2. The results are discussed in Sect. 3 and the paper is concluded in Sect. 4.

2 The Proposed Algorithm (GPS/DR/V2V)

The proposed algorithm estimates the position of the vehicles based on the information obtained through the GPS, Kinematic sensors, and information collected from neighboring vehicles through vehicle to vehicle communication (V2V). Vehicles are assumed to be equipped with Kinematic sensors such as wheel speed, steering angle, yaw rate and GPS sensors, and dedicated short range communication (DSRC) radios. Kinematic sensors are presumed to be accurate with low uncertainty with normal distribution and zero mean. Vehicles periodically broadcast the position, speed and direction after every 100 ms. Figure 1 shows the block diagram of the proposed algorithm. The detailed integration is presented in Sects. 2.1 and 2.2.

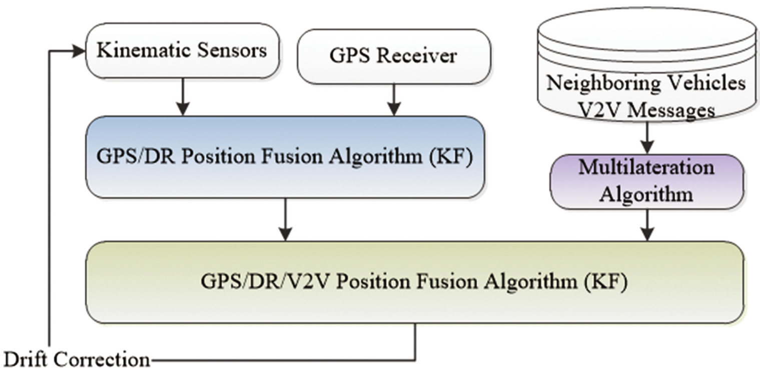

Fig. 1. Block diagram of the proposed positioning algorithm (GPS/DR/V2V)

2.1 GPS/DR Fusion Algorithm

The basic principle of Kalman Filtering is integrating data from two models namely measurements and prediction models as.

$$\begin{aligned} x_k &= F\check{x}_{k-1} + w_k \\ y_k &= Hx_k + v_k \end{aligned} \tag{1}$$

where x_k is the state vector, transition matrix F obtained from vehicles kinematic model (motion equation), w_k is the system noise with covariance Q_k. y_k is the measurement model (or observation model) that map the current vehicle stats x_k to the measurement, v_k is the measurement noises with covariance R_k. Therefore, GPS/DR fusion algorithm is derived based on KF as follows.

Step 1: State Prediction Phase: In the prediction phase, vehicle current state $\check{x}^{-}_{k|k-1}$ can be predicted as follows.

$$\begin{aligned} \check{x}^{-}_{k|k-1} &= F\check{x}_{k-1} \\ \check{P}^{-}_{k|k-1} &= F\check{P}^{+}_{k-1|k-1}F^{T} + Q_k \end{aligned} \tag{2}$$

where $\check{P}^{-}_{k|k-1}$ is the prediction uncertainties and is predicted obtained estimation uncertainties. Q_k is the process noise covariance which contains the uncertainties of the prediction model. F is the transition matrix where F^T is its transpose. Upon receiving new measurement y_k from GPS. The error $\check{z}_k$ between the actual measurement y_k and predicted measurement $\check{y}_k$ based on estimation of the priori a state $\check{x}^{-}_{k|k-1}$ can be calculated as flows.

$$\check{z}_k = y_k - \check{y}_k \tag{3}$$

where $\check{z}_k$ is the innovation sequence with theoretical covariance S_k:

$$S_k = \left(H\check{P}^{-}_{k|k-1}H^{T} + R_k\right) \tag{4}$$

Kalman gain K_k is calculated as follows.

$$K_k = \check{P}^{-}_{k|k-1}H^{T}S^{-1} \tag{5}$$

Step 2: State Correction Phase: The final estimation is a posteriori state $\check{x}^{+}_{k|k}$ at step k, can be calculated as follows.

$$\begin{aligned} \check{x}^{+}_{k|k} &= \check{x}^{-}_{k|k-1} + K_k\check{z}_k \\ \check{P}^{+}_{k|k} &= (I - K_kH)\check{P}^{-}_{k|k-1} \end{aligned} \tag{6}$$

where K_k is the Kalman Gain K_k. K_k is obtained from $\check{P}^{-}_{k}$ and H^T which were obtained from previous calculations, whereas R_k is obtained priori. R_k will be updated when there are enough measurements in the innovation sequence $\check{z}_k$. $\check{P}^{+}_{k|k}$ is the uncertainties of $\check{x}^{+}_{k|k}$ i.e. large value means high uncertain where as small value means less uncertain which is most confident.

2.2 GPS/DR/V2V Fusion Algorithm

The vehicle collects the mobility information of its neighboring vehicles using their DSRC communication device through beaconing. Vehicles are required to broadcast their mobility information every 0.1 s in order to be aware of their neighboring vehicles. Vehicles also measure the distance between its current positions with the neighboring vehicles upon receiving their mobility messages. The distance could be measured by utilizing any ringing techniques such as ToF, RSSI, Radar, Lidar, and laser among others. Once the position information of neighboring vehicles are received, a vehicle computes its position by solving a set of mathematical equations, that maps the inter vehicle distances to the distances computed from the received positions of neighbors. This algorithm is called multilateration (MLAT). The reader is referred to Boukerche, Oliveira [13] for more information. As MLAT can be inaccurate due to distance measurements limitations and the inaccuracy of neighboring vehicles' positioning information. Therefore, Kalman filter is applied to correct the MLAT prediction. Thus, similar fusion steps of GPS/DR are also applicable for fusing GPS/DR with V2V. These steps can be described into MLAT and correction phases.

Phase 1: State Prediction using Multilateration Algorithm (MLAT): In this phase, vehicles will use the output of the pervious Kalman filter based fusion and use it along with the mobility information of neighboring vehicles to further enhance their positioning. Firstly, each vehicle obtains the initial position estimation $\check{x}^{+}_{k|k}$ from GPS/DR output. The, it obtains the inter-vehicle distances using suitable ringing techniques, when the mobility information is received from neighboring vehicles. Finally, it performs MLAT to estimate the current vehicle position $y_{k(V2V)}$. The detailed description of MLAT can be found in [12].

Phase 2: State Correction Phase: In this phase, the estimated positions are improved by minimizing the error using correction phase of Kalman filter. Firstly, the discrepancy $\check{z}_k$ between the previously estimated position from GPS/DR stage $\check{x}^{+}_{k|k(GPS/DR)}$ and the position estimated by neighboring vehicle $y_{k(V2V)}$ is calculated as follows.

$$\check{z}_{k(V2V/GPS/DR)} = y_{k(V2V)} - H\check{x}^{+}_{k|k(GPS/DR)} \tag{8}$$

Then the new Kalman gain is computed as follows.

$$K_k = \check{P}^{+}_{k|k-1} H^T S^{-1} \tag{9}$$

Thus, the final estimation can be obtained as follows.

$$\begin{gathered} \check{x}^{+}_{k|k(V2V/GPS/DR)} = \check{P}^{-}_{k|k-1} + K_k \check{z}_{k(V2V/GPS/DR)} \\ \check{P}^{+}_{k|k} = (I - K_k H)\check{P}^{-}_{k|k-1} \end{gathered} \tag{10}$$

$\check{P}^{+}_{k|k}$ will be used for the next iteration as prior knowledge about the estimation error covariance.

3 Results and Discussions

The proposed GPS/DR/V2V algorithm is implemented in MATLAB. Next Generation Simulation (NGSIM) Trajectory Data (I-80) was used to evaluate the effectiveness of the proposed algorithm. NGSIM is as collection of real-world vehicle trajectory data. Figure 2 depicts the experiment's scenario. In this scenario, there are three regions. In the first one, GPS is available with an open sky and clear environment. Then, it is blocked by skyscrapers and buildings in the second region. Finally, third region is exposed to different noises due to the clouds and the weather. This scenario is used to evaluate the effectiveness of the proposed GPS/DR/V2V algorithm against the conventional GPS/DR algorithm.

Fig. 2. Experiments scenario

Ten vehicles were randomly selected from the dataset. The vehicle trajectory was replicated 20 times to generate long driving road. This replication is necessary in order to obtain long driving time period with unstable vehicles' environment. A total of 10 km road length is used in the scenario.

Figure 3 presents the results of the experiment for each tested vehicle. The x-axis holds the sample's number while y-axis contains the root mean square error RMSE value for each corresponding sample. As shown in Fig. 3, the proposed algorithm produced better accuracy than the conventional algorithm with respect to all tested samples. This is mainly due to the capability of the second stage integration to correct the dead reckoning error when the GPS is not available.

Figure 4 shows an example of the error behavior of the proposed algorithm as compared with the conventional one (GPS/DR). As shown in this figure, the RMSE of the proposed algorithm increases rapidly into 3 m in the beginning then it decreases to1.5 m. In the end of the scenario GPS/DR/V2V error increases slightly because the uncertainty of the neighboring positions are also increased. Meanwhile, the error of GPS/DR rapidly increases. The enhancement in the GPS/DR/V2V is mainly due to the utilization of the neighboring vehicles' positions.

Multilateration algorithm (MALT) accuracy is influenced by the number of messages from neighboring vehicles, the accuracy of the received information and the accuracy of the inter-vehicle distances. In contrast, the error of the conventional method

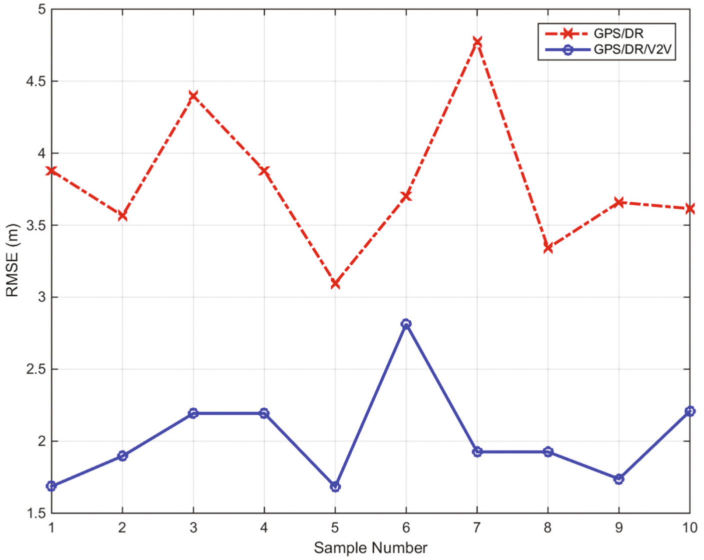

Fig. 3. Comparison of accuracy between GPS/DR/V2V and GPS/DR

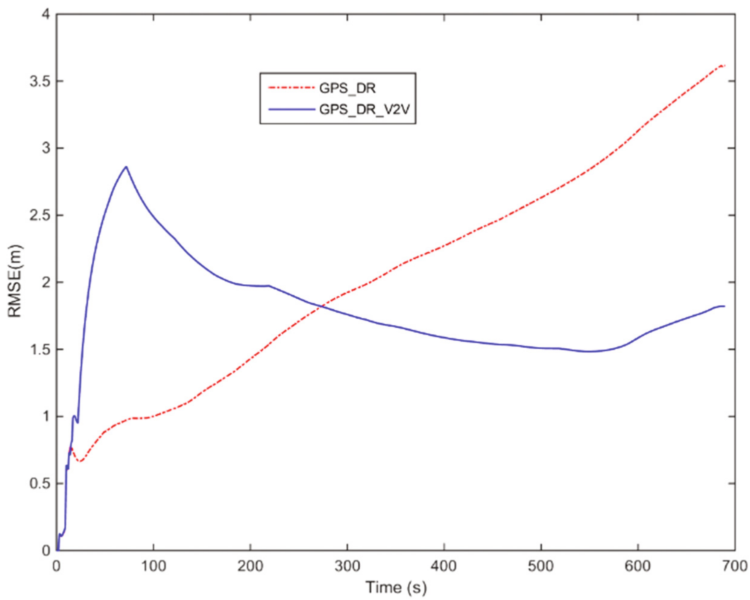

Fig. 4. Comparison of RMSE of GPS/DR/V2V and GPS/DR

is accumulated with the time. This is due to the effect of dead reckoning drift during unstable period of GPS.

4 Conclusion

Maintaining continuous and accurate positioning information is recognized as one of the major challenges in Vehicular Ad Hoc Networks. The achievable level of the positioning accuracy using existing positioning approaches does not meet the requirements of many VANET applications and services. In this paper, we further enhanced the GPS/DR integration by including cooperative mobility messages of the neighboring vehicles. Two-stage integration was proposed to ensure the continuous and accurate positioning information. The integration was performed based on two cascaded Kalman filters. First KF was used to fuse GPS information with vehicle dynamics (dead reckoning). The second KF was used to fuse the results of first KF with the neighboring mobility information. The experimental results showed that the proposed algorithm improved the accuracy of the positioning algorithm. It outperformed the conventional algorithm by 46% enhancement.

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