Proof of Concept Study Using DSRC, IMU and Map Fusion for Vehicle Localization in GNSS-Denied Environments

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Abstract—Both safety and non-safety applications of vehicular networks rely on accurate position information. However, accurate localization of a vehicle in a global navigation satellite system (GNSS) denied environment is a challenging and still open research problem. The 802.11p dedicated short-range communication systems (DSRC), designed for vehicle-to-vehicle and vehicle-to-infrastructure communications, can help to solve this problem. In this paper, we propose an algorithm to self-localize a vehicle in a GNSS-denied environment. The algorithm is designed for vehicles driving on inner city streets, which are usually made up of an amalgamation of straight and curved trajectories. Data from an inertial measurement unit and map information are fused with radio frequency time-of-arrival measurements, obtained from a single 802.11p DSRC roadside unit, to track the vehicle along both the straight and curved portions of a trajectory. A vehicular measurement campaign is conducted and the collected measurements are utilized to evaluate the performance of the algorithm. Results indicate that the proposed algorithm can efficiently localize a vehicle in GNSS-denied environments.

I. INTRODUCTION

Vehicular-to-Everything (V2X) communications have several safety applications (such as collision prevention) and non-safety applications (such as toll charging). Dedicated short-range communication (DSRC) technology designed to facilitate V2X (both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I)) communications is based on the IEEE 802.11p standard. Each vehicle is equipped with a DSRC on-board unit (OBU) that broadcasts information related to its own dynamic states, such as position, acceleration, heading, along with secondary parameters such as brakes and lights status. For safety applications, the current position of the vehicle is one of the most important information transmitted by each vehicle, since it is used by neighbouring vehicles for various safety applications [1].

Vehicle locations are typically found using the help of a global navigation satellite system (GNSS), and various commercial DSRC products have built-in GNSS receivers [2]. GNSS-based localization requires lines of sight (LOS) to at least four navigation satellites. However, in a highly built-up environment, the urban canyon effect [3] makes this impossible in many areas. Furthermore, GNSS cannot be used in sheltered areas like tunnels or covered car parks.

For GNSS-denied environments, information from various sources and sensors (such as motion sensors, maps, and radar) can be fused with radio frequency (RF) measurements from the DSRC technology, for in-car navigation systems. Since different sensors provide different information, selecting the right sensor ultimately affects the localization process and the feasibility of the fusion process. In [4]–[6], the advantages and disadvantages of various sensors are discussed. In this paper, we focus on the fusion of inertial measurement units (IMUs) and maps with RF measurements between DSRC transceivers.

Using signals-of-opportunity (SOOP) from random RF anchors as an alternative for localization in GNSS-denied environments has been proposed in the literature [7]; however, there are a lot of challenges with utilizing random RF beacons, such as unknown signal structure, unknown transmit time, and inaccurate location of anchors. DSRC technology, on the other hand, is designed for V2X communications, which makes it the most suitable source of RF localization for vehicular networks. In a DSRC based network, the location of the anchors (i.e., roadside units (RSUs) in DSRC terminology) is precisely known, and the frequency and the structure of the signal transmitted by beacons (i.e., basic safety messages (BSMs) in DSRC terminology) are also known. Moreover, there is a widespread interest in DSRC especially by US government, which plans to mandate having DSRC in every vehicle [8]. This leads to different test-beds being set up and potential widespread deployment of RSUs.

In this paper, DSRC transceivers are utilized for RF localization. RF localization is performed by measuring one or more parameters of the received RF signal (such as received signal strength, angle-of-arrival, time-of-arrival (TOA), or time-difference-of-arrival (TDOA)) at the OBU. The difference in TOA measurements of consecutively received messages along the trajectory of a moving vehicle, known as virtual TDOA (V-TDOA) [9], [10], can be used for vehicle localization (note that the method proposed in [9] bears some similarities to techniques used in synthetic aperture radars [11]).

However, a major challenge in V-TDOA is to separate the time offset caused by the drift of the local oscillator (LO) of the receiver from the time offset due to the movement of the receiver. For terrestrial vehicles, the time offsets due both to LO drift and the vehicle movement will be in the order of tens of nanoseconds, and simply ignoring the LO drift will lead to large estimation errors. Utilizing the TOAs of a periodic message sent from the transmitter, the authors in [12] designed an adaptive filtering framework to simultaneously estimate both the LO drift and the transmitter location in cellular networks.

Inertial navigation systems (INS) are self-contained dead reckoning (DR) systems which provide dynamic information.
through direct measurements from an inertial measurement unit (IMU). However, the errors due to bias, scale factors, and nonlinearity in the sensor readings result in accumulation of navigation errors with time. Traditionally, to bound the accumulation of errors, INS systems are coupled with GPS [13]. During GNSS outages, the position error growth can be substantially mitigated and the attitude accuracy can be improved if vehicular constraints are exploited [14].

Position information in terms of pure coordinates is often difficult to interpret for a driver. To assist the driver in relating the position information to a physical location, the in-car navigation system commonly displays the position of the vehicle on a map. Moreover, under normal conditions, the location and the trajectory of a car are restricted by the road network. Hence, a digital map of the road network can be used to impose constraints on the navigation solution of the in-car navigation system via map matching (MM) [15]. Note that MM is particularly difficult at junctions and built-up areas with complex routes.

The motion of the vehicle along a trajectory can be described using various models. In this paper, we utilize two motion models: constant velocity and arbitrary motion models. Constant velocity model is suitable for straight trajectories (such as highways) while arbitrary motion model is utilized to describe trajectories with turns in them (such as inner-city roads).

The main contribution of this paper is a proof of concept study fusing DSRC signals, IMU and map information to localize a vehicle in a GNSS-denied environment. To the best of our knowledge, this study is the first implementation study to fuse DSRC signals, IMU, and map information for vehicle localization. We adopt a software defined radio (SDR) platform to implement the DSRC transceivers and integrate the IMU and map fusion algorithms.

We propose an algorithm in Section III to localize vehicles driven along both straight and curved trajectories. Our algorithm is a data fusion algorithm that utilizes TOA measurements from an RSU, acceleration and angular velocity from IMU, and map information to localize a vehicle.

Similar to [14], we use vehicular constraints to bound the IMU errors. However, we also utilize the TOA measurements from a single RSU to enhance the localization accuracy. Furthermore, the heading of the road segment identified via map matching is compared to the navigation solution and used to calibrate the sensors in the system. Lastly, the estimated position is matched to the digital map to be shown to the user. Note that unlike some prior works [16], multiple OBUs do not need to cooperate with each other to achieve self-localization in the proposed algorithm.

A vehicular measurement campaign is conducted to evaluate the performance of the proposed algorithm. The results indicate that our algorithm can be successfully used to localize a vehicle following an arbitrary motion model, in a GNSS-denied environment.

The rest of the paper is organized as follows. Sensors and measurements pertaining to the proposed algorithm are studied in Section II. In Section III, the proposed algorithm itself is presented. Performance evaluation of the proposed algorithm via a vehicular measurement campaign is discussed in IV. Finally, the paper is concluded in Section V.

II. INFORMATION SOURCES AND SENSORS

In our proposed algorithm, three sources of information are utilized, namely: DSRC RSU, IMU, and maps. Each of these sources provides a set of information that is utilized in the localization process. The rest of this section is organized as follows. Extracting V-TDOA measurements from a single RSU is discussed in Section II-A, while utilizing acceleration and angular velocity from an IMU is presented in Section II-B. Finally, information obtained from maps are presented in Section II-C.

A. V-TDOA from a Single RSU

We assume a single RSU sends a basic safety message (BSM) with periodicity $T_0$. If the first message is transmitted at time $t_0$, the OBU will receive the $k^{th}$ message at time $[12]
\[ t_k = t_0 + (k-1)T_0 + \Delta t_k + \Delta \tau_k, \]
where $\Delta t_k$ is the propagation time between the RSU and the OBU, and $\Delta \tau_k$ is the time offset due to LO drift between $t_0$ and the time of measurement $k$. For a line-of-sight environment, $\Delta t_k$ is defined as
\[ \Delta t_k = \frac{(p_{nx,k} - x_R)^2 + (p_{ny,k} - y_R)^2 + (p_{nz,k} - z_R)^2}{c_0}, \]
where $c_0$ is the speed of light, $(p_{nx,k}, p_{ny,k}, p_{nz,k})$ are the $x$, $y$, and $z$ coordinates of the OBU respectively, and $(x_R, y_R, z_R)$ are the $x$, $y$, and $z$ coordinates of the RSU respectively. The local time of the OBU LO is defined as
\[ \tau_k \triangleq t_0 + (k-1)T_0 + \Delta \tau_k. \]
From (1), it is seen that if the LO time offset $\Delta \tau_k$ is zero, the V-TDOA between two successive points $\Delta t_k - \Delta t_{k-1}$ can be estimated by $t_k - t_{k-1} - T_0$. Note that it is assumed that $\Delta t_{k-1}$ is known at time $k$. However, when $\Delta t_k \neq 0$, the propagation time $\Delta t_k$ cannot be readily estimated from the measurements $t_k$ and $t_{k-1}$. To overcome this problem, the LO model from [17] is used to evaluate the evolution of the LO time offset.

B. IMU with Vehicular Constraints

In [14], a wheeled vehicle moving on the earth surface is considered. The position of the vehicle $p_n = [p_{nx}, p_{ny}, p_{nz}]^T$ is the position vector of the origin of the body frame in the navigation frame, and the velocity of the vehicle $v_n = [v_{nx}, v_{ny}, v_{nz}]^T$ is the rate of change of $p_n$. Note that the navigation frame is the coordinate frame with respect to which the location of the vehicle needs to be estimated, whereas the body frame is attached to the vehicle and is aligned with the axes of the IMU. The orientation of the vehicle is represented by the three Euler angles $\psi$ (yaw), $\theta$ (pitch), $\phi$ (roll), where the order of the rotation is about $b_z$ followed by $b_y$ and then $b_x$ respectively. The orientation of the body frame with respect
to the navigation frame is described by the rotation matrix in (3) [14], where \( cX = \cos(X) \) and \( sX = \sin(X) \).

\[
C^n_b = \begin{bmatrix}
  c\theta c\phi & s\theta c\phi & -c\phi s\psi + c\theta s\phi \\
  s\theta c\phi & -c\theta c\phi & c\phi s\psi + s\theta s\phi \\
  -s\theta & c\theta & c\phi s\phi
c\phi
\end{bmatrix}
\tag{3}
\]

The acceleration and angular velocity in the body frame are denoted by \( a_b = [a_{bx}, a_{by}, a_{bz}]^T \) and \( \omega_b = [\omega_{bx}, \omega_{by}, \omega_{bz}]^T \) respectively; these quantities can be measured by a three-dimensional (3D) accelerometer and a 3D gyroscope, respectively. By using the relation between the acceleration measured in the body frame \( a_b \) and the acceleration in the navigation frame \( a_n \), and by exploiting the kinematic relationship between \( a_n \) and the rates of changes of the Euler angles, the state equations for vehicle motion can be defined by (4) [14]. From (4), the state of OBU is tracked from an initial state and a series of measurements on \( a_b \) and \( \omega_b \) generated by an IMU.

\[
\begin{align*}
  p_n &= v_n \\
  v_n &= C^n_b a_b - g \\
  \psi &= \frac{w_{by} \sin \phi + w_{bz} \cos \phi}{\cos \theta} \\
  \dot{\theta} &= w_{by} \cos \phi - w_{bz} \sin \phi \\
  \dot{\phi} &= w_{bx} + (w_{by} \sin \phi + w_{bz} \cos \phi) \tan \theta
\end{align*}
\tag{4}
\]

Vehicle constraints (also called nonholonomic constraints in the control literature [14]) can be used in order to bound position errors due to incorrect estimates of \( a_b \) and \( \omega_b \) [13], [14]. Under ideal conditions, there is no side slip along the direction of the rear axle (y-axis) and no motion normal to the road surface (z-axis); thus, if \( v_b = [v_{bx}, v_{by}, v_{bz}]^T \) denotes the velocity in the body frame, both the y-axis and z-axis velocities (i.e., \( v_{by} \) and \( v_{bz} \), respectively) are equal to zero. However, these constraints can be violated due to the presence of many factors such as noise. Since \( v_b = (C^n_b)^T v_n \), the constraints can be formulated by (5), where \( \eta_y \) and \( \eta_z \) are zero mean Gaussian noises on the y-axis and z-axis velocity constraints respectively.

\[
\begin{align*}
  v_{by} &= v_{bx} (s \phi \sin \theta \psi + c \phi \cos \psi) + v_{by} (s \phi \sin \theta \psi + c \phi \cos \psi) + \eta_y \\
  v_{bz} &= v_{bx} (c \phi \sin \theta \psi + s \phi \cos \psi) + v_{by} (s \phi \sin \theta \psi - c \phi \cos \psi) + \eta_z
\end{align*}
\tag{5}
\]

C. Map Matching

The digital map used in car navigation systems and other ITS applications are built up as databases of topological (connectivity properties of the features in the map) and coordinates information, together with attributes such as road class, street name, expected driving speed, and turn restrictions. A road network representation, \( N \), consists of a set of curves in \( \mathbb{R}^2 \), each of which is called an arc. Each arc is composed of linear line segments (LSs) [18].

We utilize a digital map where the roads are divided into line segments, and each LS has a start and an end point. Each of these points is represented by \( x-y \) coordinates in the Universal Transverse Mercator (UTM) frame, along with the corresponding road attributes. Note that whenever there is a turn in the road, a new LS is started and completed. Therefore, the length and number of LSs used to represent a road depend on the geometry of the road.

Due to sparse digitization, position obtained from map data might include errors (offset) with respect to the ground truth. Therefore, using the map as a position measurement can bias the estimation process. On the contrary, these biases do not affect the heading information since the map relative precision is often good. The accumulated error in DR systems is dependent on the quality of the heading estimate. Thus, we use heading information of the map as an observation in the filtering process.

In order to get a map heading, an initial road selection stage has to be addressed. A small area is extracted from the navigable road database based on the estimated vehicle location. This is important for real-time operation with limited processing resources. To extract the navigable roads, we use point-to-curve map matching which matches the estimated position with the closest curve in the network [15]. Then, the segment heading is determined using the geometrical points of the road and the driving direction of the vehicle, as will be discussed in Section III.

III. PROPOSED ALGORITHM

The proposed algorithm is designed for an arbitrary motion model, which is suitable to model any trajectory (either straight or curved) and for variable speeds. The vehicle state along with TOA related parameters are defined by the vector \( x = [p^T_k, v^T_k, \alpha^T, \tau, \beta]^T \) (11-dimensional vector) where \( \alpha = [\phi, \theta, \psi]^T \) and \( \beta \) is the clock skew between the RSU and the OBU clocks. The kinematic relationships (4), for sufficiently small sampling intervals (\( t_s \)), can be linearized by incorporating all the elements of the direction cosine matrix \( C^n_b \) into the state equations themselves. Hence, the state-space model of the Extended Kalman Filter (EKF) used in the proposed algorithm is

\[
x_k = f(x_{k-1}, u_k) + \nu_x(Q),
\tag{6}
\]

where \( f(x_{k-1}, u_k) \) is defined in (7), \( u_k = [a_{by}^T, a_{bz}^T]^T \) is the input vector, \( \nu_x(Q) \) is the zero mean additive Gaussian noise vector with covariance matrix \( Q \).

\[
\begin{align*}
  p_{nk} &= p_{nk-1} + t_s v_{nk-1} \\
  v_{nk} &= v_{nk-1} + t_s (C^n_{by} a_{by} - g) \\
  \alpha_k &= \alpha_{k-1} + t_s (\Phi_{k-1} a_{by} - g) \\
  \gamma_k &= \gamma_{k-1} + t_s \beta_{k-1} \\
  \beta_k &= \beta_{k-1}
\end{align*}
\tag{7}
\]

Note that \( \Phi_{k-1} \) is defined in (8).

\[
\Phi_{k-1} = \begin{bmatrix}
  0 & \sin \phi & \cos \phi \\
  \cos \theta & \cos \phi & -\sin \phi \\
  0 & \cos \theta & \sin \phi \\
  0 & \sin \tan \theta & \cos \tan \theta
\end{bmatrix}_{k-1}
\tag{8}
\]
the vehicle. Finally, the updated position of the vehicle is projected onto the map and outputted to the user. Spatial sampling of the roads can be insufficient in certain areas due to database simplifications. These simplifications can lead to a poor vehicle heading estimation in a curve depicted by only a few segments for instance. Hence, the consistency of the selected LS must be assessed before map information fusion, which is checked in the same manner as TOA data. The proposed algorithm is summarized in Table III.

TABLE I

<table>
<thead>
<tr>
<th>Proposed Algorithm: Arbitrary Motion Localization</th>
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<tbody>
<tr>
<td>1: Initialize (position, velocity, attitude)</td>
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<tr>
<td>2: Predict state vector based on IMU inputs</td>
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<tr>
<td>3: Update state vector with TOA measurements and Vehicle Constraints</td>
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<tr>
<td>4: Compute road selection and map heading</td>
</tr>
<tr>
<td>5: Update state from Step 3 with map heading in Step 4</td>
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<tr>
<td>6: Project estimated position on the nearest LS and output position to the user</td>
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<tr>
<td>7: Go to Step 2</td>
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</tbody>
</table>

IV. VEHICLE TEST SETUP AND RESULTS

To evaluate the performance of our proposed algorithm, we conducted a vehicular measurement campaign. The setup used in the measurement campaign is discussed in Section IV-A, while the performance evaluation results are presented in Section IV-B.

A. Measurement Setup

The main objective of the vehicular test is to collect measurements between a single RSU and a single OBU, which could be used to estimate the TOA of messages along a trajectory. Additionally, for each trajectory, IMU and GPS data have to be collected. Note that IMU data are utilized in the proposed algorithm, which was discussed in Section III. GPS data, on the other hand, is not used in the localization process; rather, it is utilized as a benchmark for performance evaluation and for initialization.

Fig. 1. Measurements setup.

Fig. 1, shows the block diagram of the measurement setup. Two Ettus N210 USRPs (universal software radio peripherals) are utilized as transceivers for the RSU and OBU. The USRPs are equipped with GPSDO modules,
which (even when disconnected from GPS) provide a high-quality oven controlled crystal oscillators with an accuracy of 1-10 parts-per-billion. One USRP is located in the street as an RSU, while the second USRP is inside the vehicle. A UBX 10-6000 MHz Rx/Tx daughter board (frequency range: 10 MHz - 6 GHz) is installed in each of the N210 USRPs.

The RSU is set to periodically transmit an IEEE 802.11p frame. To achieve this, we generated an OFDM frame based on the IEEE 802.11p standard and pad it with zeros, such that the duration of the OFDM symbol is 1 ms (0.2 ms data, 0.8 ms zero padding). Note that the sampling frequency set by the IEEE 802.11p standard is 10 MHz. Thus, the transmitted OFDM frame is composed of $10^3$ samples.

The transmitting USRP is set to continuously transmit this frame for the duration of the measurement.

The OBU, on the other hand, is set to periodically receive the aforementioned IEEE 802.11p frame. This is achieved by setting the USRP in the vehicle to save $10^3$ samples every $T_0 = 100$ ms. Additionally, the USRP in the vehicle, along with an EVK-M8T UBLOX GPS and a Xsens MTi-10 series IMU, are connected to a laptop as shown in Fig. 1. Angular velocity and acceleration from the IMU are recorded every 5 ms and are utilized in our proposed algorithm. Data collected from GPS (at a rate of 10 Hz) are only used for initialization and as a benchmark.

B. Results

The received DSRC messages, along with the IMU data and GPS data are processed offline. From the received DSRC messages, the TOA is estimated in two steps. First, by correlating each DRSC message with the known long training sequence (LTS) a coarse estimate of the TOA can be determined. After which, utilizing quadratic interpolation, a finer estimate (i.e., higher resolution) of TOA is achieved. In quadratic interpolation, the correlation function is estimated by a parabola in the neighborhood of its maximum [19].

The proposed algorithm is designed for vehicles driven along inner city roads, which are usually made up of straight and curved trajectories. Thus, to evaluate the performance of the proposed algorithm, IMU measurements (angular velocity and acceleration) are fed to the EKF, along with the TOA measurements. In addition, MM was performed as a second update stage in the EKF. The EKF utilized in the proposed algorithm is initialized via the position, velocity, and attitude obtained from GPS. Note that GPS data is not used any further in the localization process. For the MM portion of the algorithm, the LS selection radius $r$ is set to 100 m, while the heading threshold $\psi_{th}$ is set to 40 degrees.

Figs. 2 and 3 show the performance of the proposed algorithm for two trajectories. The first trajectory, which is shown in Fig. 2, has only a single turn; however, the second trajectory shown in Fig. 3 includes two turns. Both Figs. 2 and 3 show the performance of estimated trajectories versus the trajectories obtained by GPS. In both cases, by utilizing the proposed algorithm we are able to localize the vehicle in the absence of GPS. Additionally, the achieved accuracy is within 1 to 5 m. Note that despite using erroneous

![Fig. 2. Performance of proposed algorithm for a trajectory with one turn.](image)

![Fig. 3. Performance of proposed algorithm for a trajectory with two turns.](image)

![Fig. 4. Performance of proposed algorithm for a straight trajectory.](image)

For a vehicle driven along a straight trajectory (i.e., with nearly constant velocity), our proposed algorithm can
localize the vehicle by utilizing only TOA measurements. Since the velocity of the vehicle does not change along the trajectory, information from IMU and maps are not required. In this case, only TOA measurements are fed to the EKF, where the EKF is initialized with the position and velocity of the vehicle obtained from the GPS; after which, the GPS data is not used for the rest of the localization process. Fig. 4 shows a trajectory estimated by our proposed algorithm, where IMU and map information are not available, versus the same trajectory obtained from GPS. Fig. 4 indicates that a vehicle driving along a straight trajectory can be localized via DSRC messages from a single RSU. However, it was found that initializing the EKF with accurate position and velocity values is essential.

Finally, the findings from utilizing the rest of the collected data in evaluating the performances of the proposed algorithm for various trajectories are:

1) Properly initializing the EKF is more important if IMU and map information will not be utilized (i.e., for straight trajectories). This is due to the fact that for a straight trajectory, the proposed algorithm relies only on a single TOA measurement and under the assumption of a constant velocity.

2) The better the TOA measurements, the better the performance of the algorithms.

3) Achieved accuracy varies from one trajectory to another and from one portion of the trajectory to another. Factors that affect accuracy are the quality of TOA, the accuracy of digitized maps, and the quality of IMU measurements.

V. CONCLUSION

A proof of concept study that fuses DSRC along with IMU and map information to localize a vehicle in GNSS-denied environments has been presented in this paper. An algorithm has been proposed that fuses TOA measurements from DSRC RSUs with IMU and map information; thus, it is more suitable for vehicles driven on inner-city roads (i.e., trajectories that follow arbitrary motion model). In the proposed algorithm, we bound the navigation errors of the IMU by vehicle constraints and TOA measurements. Moreover, we exploit map data for robust localization. Additionally, it was shown that for vehicles driven on highways (i.e., straight trajectories), our proposed algorithm only requires TOA measurements from a single RSU to localize a moving vehicle. The performance of the proposed algorithm is evaluated via a vehicular measurement campaign and the validation results show the effectiveness of the proposed algorithm in localizing a moving vehicle in GNSS-denied environments.

REFERENCES


