RSSI/IMU Sensor Fusion-Based Localization Using Unscented Kalman Filter

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***Abstract*—The most crucial problem in navigation system is localization. The global positioning system (GPS) has long been used in mobile unit localization. However, GPS is incapable in some situation such as indoor environment. The received signal strength indicator (RSSI) from wireless communication is a promising alternative method to derive the location of a mobile unit. To improve the precision and robustness in the GPS-based localization, an inertial measurement unit (IMU) is normally used. In this paper, we study the possibility to use RSSI from wireless local area network (WLAN) and an IMU to derive the location of the mobile unit. We apply unscented Kalman filter (UKF) as a fusion engine for those two information. The experiment is conducted by using mobile unit equipped with low-cost IMU and a wireless communication module together with multiple access points to evaluate the performance of our algorithm, and the result is promising.**

Keywords: Localization, RSSI, IMU, unscented Kalman Filter

I. Introduction

Mobile unit localization is the most fundamental and important problem in many applications such as unmanned autonomous vehicles, mobile robots in explore, search and rescue operation, asset tracking in warehouse, etc. There has been extensive research in this area. There are various types of sensors and approaches for deriving the position and orientation, also known as pose, of the mobile unit. In general, however, we can classify those sensors into two types, namely relative position or inertial sensors and absolute position sensors. We refer the reader to [1], [5] for a survey.

The relative sensor, such as an IMU, provides implicit pose's information relative to an initial pose. The pose is, then, obtained by integrating those information, and, hence, it normally suffers from bias that, even a tiny, causes huge error in long run which is also known as drift. This drift can be reduced by certain schemes to reset an error intermittently. The advantage of this type of sensor is that it relies on its own system not on other references or outside environment that cannot be manipulated.

The absolute sensor provides information on a distance or an orientation relative to known-position references. Multiple references are required to locate the mobile unit—for example, three distances or angles are necessary to identify a unique position in two-dimensional plane known as trilateration and triangulation. Currently, the most widely used localized method based on relative distance is the GPS, in which distances from at least four references (satellites) are required to identify a unique position of an object in 3-dimensional space. In trilateration, a distance may inherit from time of flight (TOF) of a beacon signal from a reference. Hence it requires very precise time synchronization and measurement. Another way to obtain distance is from power loss of a beacon signal. This method, as used in this paper, is recently received much attention, since it is relatively low cost due to the vast availability of wireless communication system in both outdoor and indoor environment. This absolute sensor based method relies on wireless communication link between a mobile unit and remote references, so it normally suffers from the loss of communication or interference from outside environment such as in tunnel or building. The localization method, however, has no drift effect since there is no integration requirement.

Most of the practical navigation system, however, makes use of the advantages of both relative and absolute sensors, for example GPS/IMU/INS sensor fusion, particularly for low cost devices, in which huge amount of research can be found; see, e.g., [2], [3], [10], [19]. There are also many localization methods dealing with various types of sensor fusion; for example, in [4], the distance induced from TOF of data packet from ultra wide band (UWB) communication is used to handle the drift effect from IMU sensors in pose estimation of human gesture. In [17], [18] the visual sensing and IMU are used in pose estimation of mobile robot. Recently published paper [8] provides comprehensive review of various methods for general sensor fusion.

When GPS is invalid, the transmitted power loss form wireless communication link, or RSSI, is a promising method to derive a distance from a reference. The localization based on RSSI has been the popular research topic for a few decade due to the widely use of wireless communication in mobile phone and WLAN. Furthermore, in most indoor environment, there are many WLAN transmitters that can be used without additional cost.

There have been researches on RSSI-based localization in logistic applications to track products, assets or equipments. For example, in [21], the RSSI is used in multilateration scheme in wireless sensor network in food transportation. Also, the paper [22] proposes the localization scheme based on spatial reasoning filter using several sensor nodes in various directions—by moving sensor nodes—which is opposing to temporal filter that acquires multiple RSSI at the same location. Similar application can be found from the paper [9] that studies and testes various localization method to track the material in construction site.

The recent work on RSSI/IMU-based localization can be found in [23], where it applies the particle filter as a localization algorithm to track a pedestrian with foot-mounted IMUs and using RSSI from WiFi access points to compensate the drift. The paper also uses the precise model of the map to constraint or narrow down the location possibility of the pedestrian. Another key important idea is that the way to detect when the pedestrian stop walking and then the velocity is reseted in both longitudinal and lateral directions to reduce drift error.

The fusion scheme needs nonlinear filtering technique to handle this nonlinearity from the RSSI measurement. Most widely used method is the linearized version of the Kalman filter known as extended Kalman filter (EKF). For instance, the RSSI-based localization that uses the robust extended Kalman filter (EKF) can be found in [12], [13]. The former paper deals with the tracking of cellular phone user in the service cells to improve quality of service. The results are presented by simulation. The later paper proposes the localization method to locate the mobile robot. The experimental results are based on dedicated wireless communication links that can measure the receiving analog power signal directly which is opposing to our system that obtains the RSSI with low sampling rate and high quantization noise.

In the past decade, the unscented Kalman filter (UKF) has been proposed to replace the EKF. In the paper [7], Julier and Uhlmann demonstrated that the UKF performs better than the EKF. Many research later adopted this method in various non-linear filtering and reported the same conclusion, see e.g., [11]. In this work, we study the possibility of using sensor fusion from a low cost IMU and RSSIs by applying the UKF for mobile unit localization in two-dimensional plane. The information from an IMU—velocity, in this case— suffers a tiny bias causing drift error in long run. On the other hand, the information on an RSSI, based on IEEE802.11b standard, is corrupted by large multi-path fading effect and quantization noise. The test bed is performed in indoor environment by moving the mobile platform in the predefined path repeatedly to verify the accuracy of algorithm.

The body of the paper is organized as follows. In section II, we address the problem by using simple kinematic model of moving object and characterize the measurement equations from both sensors. In section III, we briefly present the UKF algorithm. The experimental results will be presented in section IV, and the conclusions are drawn in section V to sum up our work.

II. System Modeling

The fusion scheme is based on the Kalman filter, so we need the state space description of the system dynamics and measurement model as follows.

A. Process Model

The simplified process of the moving object will be used; that is the kinematic of the mobile unit including position and velocity. Now, let p^x, p^y, v^x, v^y denote position and velocity in x and y direction in the Cartesian space respectively, and let $x = \begin{bmatrix} p^x & p^y & v^x & v^y \end{bmatrix}^T$. In this note, we assume that the control signal, denoted by u, is unknown, and hence will be considered as an uncertainty. Now consider the kinematic model of the vehicle in discrete-time as follows:

$$x_{k+1} = Ax_k + Bu_k, \quad \forall k \in \mathbb{Z}^+, \tag{1}$$

where

$$A = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ T & 0 \\ 0 & T \end{bmatrix},$$

and T is the sampling time. The objective is to estimate the position of above mobile platform from an IMU and an RSSI sensing systems.

B. IMU Measurement Model

The IMU, using in this work, is a low-cost microcomputer embedded system that provides the information of linear velocity and attitude. In our study, however, we use only the velocity output. Hence, from above state space representation, we can describe measurement equation from the IMU as follow:

$$y_k^I = \begin{bmatrix} 0 & 0 & -\sin\theta & \cos\theta \\ 0 & 0 & \cos\theta & \sin\theta \end{bmatrix} x_k + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} b^x \\ b^y \end{bmatrix} + v_k^i, \tag{2}$$

where θ is the alignment angle between any reference frame and the IMU reference frame measuring relative to the Earth magnetic north pole, b^x and b^y are bias noises, and v_k^i is measurement noise.

Since the bias noises have significant impact, so it is common in localization scheme that the bias noises are modeled as constants or slowly changing values, and then can be incorporated into the system modeling. That is, let $x := \begin{bmatrix} p^x & p^y & v^x & v^y & b^x & b^y \end{bmatrix}^T$ be the augmented state. Hence, we can modify the state space description as follow:

$$x_{k+1} = Ax_k + Bu_k + w_k, \quad \forall k \in \mathbb{Z}^+, \tag{3}$$

where w_k could be considered as uncertainties or disturbances to the system, in particular to the bias state, and

$$A = \begin{bmatrix} 1 & 0 & T & 0 & 0 & 0 \\ 0 & 1 & 0 & T & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ T & 0 \\ 0 & T \\ 0 & 0 \\ 0 & 0 \end{bmatrix}.$$

Therefore, the measurement equation from IMU can be rewritten by

$$y_k^I = \begin{bmatrix} 0 & 0 & -\sin\theta & \cos\theta & 1 & 0 \\ 0 & 0 & \cos\theta & \sin\theta & 0 & 1 \end{bmatrix} x_k + v_k^i. \tag{4}$$

From our experiment, it is obvious that even a tiny bias from the IMU, as seen in figure 1, makes a significant drift in position as depicted in figure 2.

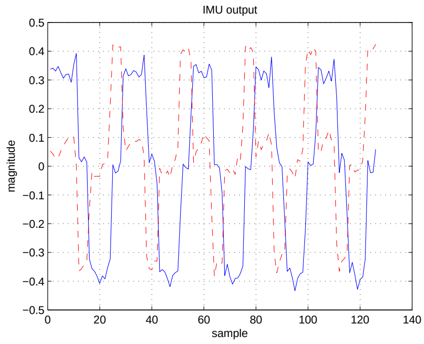


Fig. 1. Output (velocity) from IMU in both directions

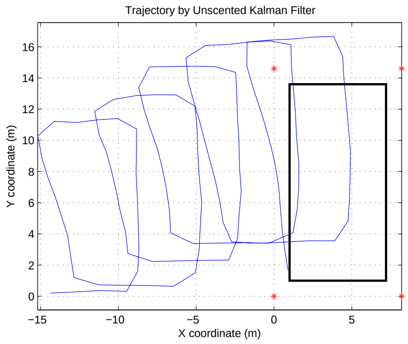


Fig. 2. Reconstructed map from IMU output only

C. RSSI Measurement Model

It is well known in the radio communication that transmitted power loss—known as path loss—at the receiver side is related to distance between them. The relation between RSSI and distance is described by ([15], [20])

$$P_r = P_0 - 10\gamma \log_{10}(d) + v_k^r, \tag{5}$$

where P_r is the power at the receiver side in dB, P_0 is a constant depending on transmitted power, antenna characteristic and average channel attenuation, γ is a path loss exponent, and v_k^r is a measurement noise dominated by shadowing fading; see., e.g., [13], [15]. From above equation, two major uncertainties, in characterizing the distance d, are the path loss exponent and the shadowing fading. The path loss exponent γ—in the open space $\gamma = 2$, for example—is dependent on environment; for example, it may be in the range of 1.6-3.5 in an office; see, for example, Table 2 in [15] or Table 4.2 in [14]. The shadowing fading or multipath fading causes unexpected high power at the receiver that averages them from multiple received data packets. The example of the RSSI measured versus distance is shown in the figure 3, in which large variation is obviously observed. Also, in figure 4, the measured RSSI during the experiment comparing with the ideal one computed by using reference moving path shows significant effect of shadowing fading that causing abnormally high RSSI.

Now the above equation can be used to characterize our measurement equations that using multiple references. Let (p_i^x, p_i^y) denote the position of the ith reference. Then we can

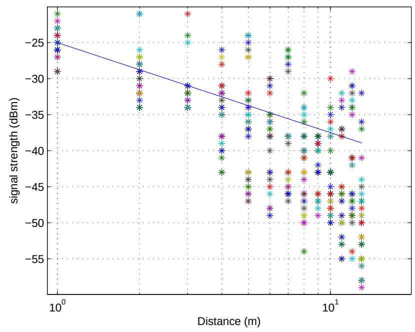


Fig. 3. Example of RSSI versus distances; solid line is approximate model: $P_r = -25 - 25\log_{10}(d)$.

define the measurement equations from RSSI, for $i = 1, 2, \ldots$, related to system state as

$$y_k^{ri} = P_0 - 10\gamma \log_{10}(\sqrt{(p^x - p_i^x)^2 + (p^y - p_i^y)^2}) + v_k^r. \tag{6}$$

In our experiment, we use four access points as the reference nodes.

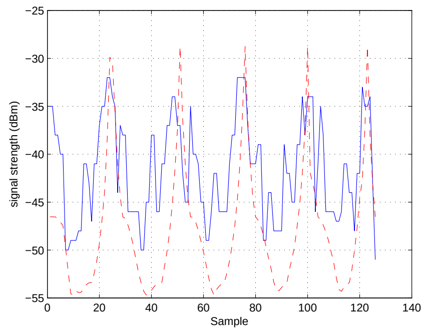


Fig. 4. RSSI from one of reference access point during experiment (solid line) comparing to ideal one (dash line) inheriting from reference path.

III. Unscented Kalman Filter

Recently, the UKF is widely used, instead of the EKF, in nonlinear filtering and estimation, particularly in robot localization area. The difference between the UKF and EKF is that the propagated process and measurement noise covariance computation. In the UKF, the points around the mean, called sigma points, are deterministically selected to capture the covariance of the process noise and, together with the mean, propagated to the next sampling time by general nonlinear function according to system's dynamics, known as unscented transform, while, in the EKF, the propagation is based on linearized model; see e.g., [6], [7], [24]. After propagating, both process and measurement noise covariances is determined by statistically calculation as well as the cross-covariance between process and measurement noise. Then the Kalman gain is computed based on those covariances, and the state is then updated similarly to the conventional Kalman filter. The concept of unscented transform that can capture the higher statistic moments or higher order terms in the Talor's series approximation makes the UKF is more robust to nonlinearity than the EKF which uses only first two terms of the Talor's series approximation. For computation cost, the main difficulty of UKF is that to find the square roots of the matrix, but, in return, it does not need to compute the Jacobian matrix as in EKF. Now, consider the following general nonlinear systems:

$$\begin{aligned} x_{k+1} &= \mathcal{F}_k\left(x_k, u_k, k\right) + w_k; \\ y_k &= \mathcal{H}_k\left(x_k, k\right) + \nu_k, \end{aligned} \tag{7}$$

where w_k and ν_k are process and measurement noises respectively. These noises are assumed to be white Gaussian noise with known covariance as $\mathrm{E}[w_k \cdot w_k^T] = Q_k$ and $\mathrm{E}\left[\nu_k \cdot \nu_k^T\right] = R_k$, where $\mathrm{E}\left[\cdot\right]$ denotes the mathematic expectation. In our case, w_k could be considered as the uncertainty from inaccurate modeling. In practice, these noise covariances serve as tuning parameters of the filter, and could be adjusted based on the empirical experiment. In addition, we assume that $\mathrm{E}\left[x_0\right] = \eta$ and $\mathrm{E}\left[\left(x_0 - \eta\right)\left(x_0 - \eta\right)^T\right] = \Xi$. Then, the UKF could be summed up as follows:

Sigma points computation

$$\begin{aligned} \chi_k^{(0)} &= \hat{x}_k; \\ \chi_k^{(i)} &= \hat{x}_k + (-1)^i \left(\sqrt{\frac{n}{1-\omega^{(0)}} P_k}\right)_i; \\ \omega^{(i)} &= \frac{1-\omega^{(0)}}{2n}, \ \forall i = 1, 2, \ldots, 2n, \end{aligned} \tag{8}$$

Propagation of mean and covariance

$$\begin{aligned} \chi_{k+1}^{(i)} &= \mathcal{F}_k\left(\chi_k, u_k, k\right), \ \forall i = 0, 1, \ldots, 2n; \\ \hat{x}_{k+1}^- &= \sum_{i=0}^{2n} \omega^{(i)} \chi_{k+1}^{(i)}; \\ P_{k+1}^- &= \sum_{i=0}^{2n} \omega^{(i)} \left(\chi_{k+1}^{(i)} - \hat{x}_{k+1}^-\right)\left(\chi_{k+1}^{(i)} - \hat{x}_{k+1}^-\right)^T \\ &\quad + Q_k. \end{aligned} \tag{9}$$

Measurement update

$$\begin{aligned} \tilde{y}_{k+1}^{(i)} &= \mathcal{H}_{k+1}\left(\chi_{k+1}, k+1\right), \ \forall i = 0, 1, \ldots, 2n; \\ \hat{y}_{k+1} &= \sum_{i=0}^{2n} \omega^{(i)} \tilde{y}_{k+1}^{(i)}; \\ \Psi_{k+1} &= \sum_{i=0}^{2n} \omega^{(i)} \left(\tilde{y}_{k+1}^{(i)} - \hat{y}_{k+1}\right)\left(\tilde{y}_{k+1}^{(i)} - \hat{y}_{k+1}\right)^T + R; \\ \Phi_{k+1} &= \sum_{i=0}^{2n} \omega^{(i)} \left(\chi_{k+1}^{(i)} - \hat{x}_{k+1}\right)\left(\tilde{y}_{k+1}^{(i)} - \hat{y}_{k+1}\right)^T; \end{aligned} \tag{10}$$

$$\begin{aligned} K_{k+1} &= \Phi_{k+1} \Psi_{k+1}^{-1}; \\ \hat{x}_{k+1} &= \hat{x}_{k+1}^- + K_{k+1}\left(y_{k+1} - \hat{y}_{k+1}\right); \\ P_{k+1} &= P_{k+1}^- + K_{k+1} \Psi_{k+1} K_{k+1}^T; \end{aligned} \tag{11}$$

where $\chi_k^{(i)}$ is the ith sigma point, n is the dimension of the system, $\left(\sqrt{\frac{n}{1-\omega^{(0)}} P_k}\right)_i$ is the ith row of the square roots of the matrix $\sqrt{\frac{n}{1-\omega^{(0)}} P_k}$ and $\omega^{(i)}$ is ith weighting factor. Note that $\sum_{i=0}^{2n} \omega^{(i)} = 1$, and $\omega^{(0)}$ is the given weighting factor corresponding to the mean. Note that, the above weighting factor is the simplest way to tune, the more sophisticated way that can effectively capture higher statistical moment can be found in [16].

IV. Experimental Results

In our experiment, we manually move the wheel mobile platform equipped with the IMU, the WLAN receiver communicating to four access points. The IMU used in this experiment is aMG IMU-9A having three-axis accelerometers chip set LSM303DLH, three-axis gyroscope chip set L3G4200D and a magnetometer chip set LSM303DLH. The velocity is then derived from the IMU raw data. The wireless communication is the IEEE802.11b standard with 2.4GHz carrier frequency with access point model Aolynk WAP500ag.

The experiment is conducted by moving the mobile platform in the predefine rectangular path for five rounds. The UKF is performed, where dynamics $\mathcal{F}_k$ equals to (3) with sampling time $T = 4$ second, and measurement equation $\mathcal{H}_k$ is from (4) and (6); that is

$$\mathcal{H}_k = \begin{bmatrix} -\hat{x}_3 \sin\theta + \hat{x}_4 \cos\theta + \hat{x}_5 \\ \hat{x}_3 \cos\theta + \hat{x}_4 \sin\theta + \hat{x}_6 \\ -25 - 25\log_{10}\left(\sqrt{\hat{x}_1^2 + \hat{x}_2^2}\right) \\ -25 - 25\log_{10}\left(\sqrt{\hat{x}_1^2 + (\hat{x}_2 - 14.6)^2}\right) \\ -25 - 25\log_{10}\left(\sqrt{(\hat{x}_1 - 8.2)^2 + (\hat{x}_2 - 14.6)^2}\right) \\ -25 - 25\log_{10}\left(\sqrt{(\hat{x}_1 - 8.2)^2 + \hat{x}_2^2}\right) \end{bmatrix},$$

where $\theta = 0.1$ rad. The UKF parameters are of follows:

$$Q = \mathrm{diag}\left(1, 1, 1, 1, 10^{-5}, 10^{-5}\right) \times 10^{-4},$$

$$R = \mathrm{diag}\left(2 \times 10^{-3}, 2 \times 10^{-3}, 10, 10, 10, 10\right),$$

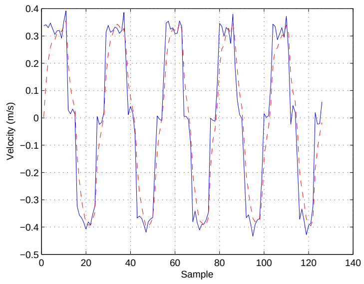
$\hat{x}_0 = \begin{bmatrix} 1 & 1 & 0 & 0.1 & 0 & 0 \end{bmatrix}^T$ and $P_0 = 10^{-3} I_{6\times 6}$, and the weighting factor $\omega^0 = 0.1$. The experimental data from IMU is shown in figure 1, and the comparison to output from the UKF is shown in figure 5. Also, the comparisons of actual RSSIs with the estimated one are depicted in figure 6.

The estimate position in x-y coordinate from the UKF is plotted together with the reference moving path in figure 7. Also, the absolute error in both x and y direction is shown in figure 8, and the root mean square errors (RMS) are 0.75 meter in x direction and 1.04 meter in y direction.

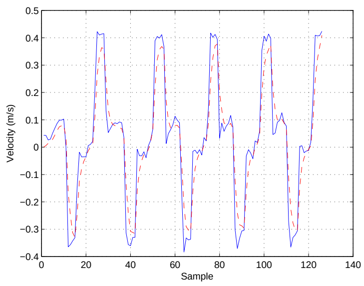
The bias states in both directions are shown in figure 9, and the trace of error covariance (P) is depicted in figure 10. Note that, the covariance matrix P is normally used to indicate the convergent of the filter, and, hence, is useful in the tuning process.

V. Conclusions

This paper studies the possibility of using RSSI/IMU sensor fusion for a mobile unit localization by using the UKF as a fusion algorithm. The results, achieving around 1 meter RMS in both direction, show that this sensor fusion scheme is a promising technique that can handle the bias problem from the IMU, and is robust to various uncertainties from the RSSI

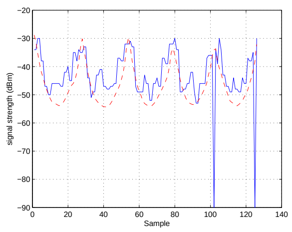


(a) x-direction

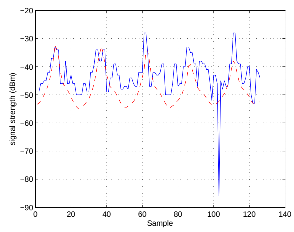


(b) y-direction

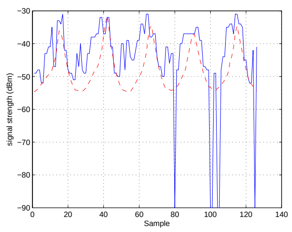
Fig. 5. Estimated (dash line) and actual IMU (solid line) output comparison.



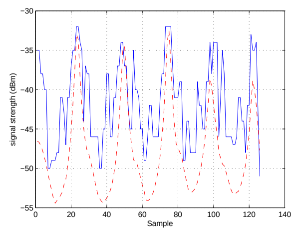
(a) access point no.1



(b) access point no.2



(c) access point no.3



(d) access point no.4

Fig. 6. Estimated (dash line) and actual RSSI (solid line) output comparison.

measurement, in particular the path loss exponent. The UKF as similar to EKF, however, need some parameters to tune including process and measurement noise covariances Q, R, as well as the weighting factor ω^0. For the future work, we will work on the method to calibrate some parameters in measurement, such as P_0, γ autonomously, or some adaptive schemes can be adopted to adjust parameters such as Q, R on-line. The future work will also involve reducing the number of reference nodes.

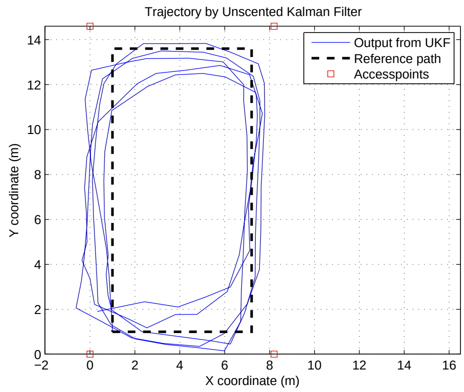


Fig. 7. Reconstructed map from the result of RSSI/IMU sensor fusion.

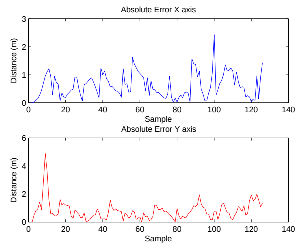


Fig. 8. Absolute error in both x and y directions.

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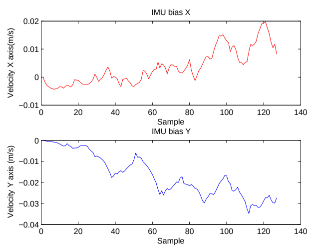

Fig. 9. IMU bias state in both x and y directions.

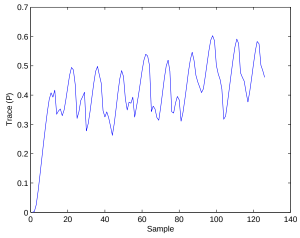

Fig. 10. The trace of error covariance (trace(P_k)).

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