Indoor Robot Localization by RSSI/IMU Sensor Fusion

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***Abstract*—Localization is the crucial problem for mobile robot navigation. For indoor mobile robot, since a global positioning system (GPS) is incapable, another promising technique to detect the position is the received signal strength indicator (RSSI) from wireless communication. To improve the precision and robustness of mobile unit localization, an inertial measurement unit (IMU) is normally used. In this report, we propose the algorithm for mobile robot localization based on sensor fusion between RSSI from wireless local area network (WLAN) and an IMU. The proposed fusion scheme is based on the extended Kalman filter (EKF). The experiment is conducted by using mobile unit equipped with low-cost IMU and a wireless communication module together with access points to evaluate the performance of our algorithm, and the result is promising.**

Keywords: Localization, RSSI, IMU, 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. Since past few decades, there has been extensive research in this area. Depending on various types of sensor, there are many approaches for localization. In general, however, there are two types of sensor using in localization, namely relative position or inertial sensors and absolute position sensor . We refer the reader to [2], [6] for a survey.

The relative sensor, e.g., an odometer and an IMU or an inertial navigation system (INS), provides the implicit pose's information relative to initial pose. The method to obtain a pose of an object, then, involves in integration, and, hence, suffers from bias that, even a tiny, causes huge error in long run. Certain schemes need to be used 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 the information on the distance or orientation relative to known-position references. In theory, it requires multiple references in localization based on these sensors—for example, three distances or angles are necessary to identify a unique position in two-dimensional plane. These methods are also known as trilateration in distance based and triangulation in orientation based. 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. For trilateration, the distance information may inherit from time of flight of the beacon signal from references. Hence, it requires very precise time synchronization between references and a mobile unit, as in, for example, the GPS. Another way to obtain distance is from power loss of the beacon signal from references. 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 require.

Most of practical navigation system, however, makes use of advantages from both relative and absolute sensors as a complementary to their weakness, for example GPS/IMU/INS sensor fusion, particularly for low cost devices, in which huge amount of research can be found; see, e.g., [3], [4], [9], [17]. There are also many localization methods dealing with various types of sensor fusion; for example, in [5], the distance induced from time of flight of data packet from ultra wide band (UWB) communication is used to handle the drifting effect from IMU sensors in pose estimation of human gesture. In [15], [16] the visual sensing and IMU are used in pose estimation of mobile robot. Recently published paper [7] provides comprehensive review of various methods for general sensor fusion–not particular for navigation purpose or certain types of sensor.

Since the GPS system is incapable for indoor environment due to communication disruption, the transmitted power loss form wireless communication link, or RSSI, is, therefore, a

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promising method to derive distances from known-position references. The localization based on RSSI has been a popular research topic for a few decade due to the widely used of wireless communication in mobile phone as well as WLAN. Furthermore, in most indoor environment, there are many WLAN transmitters that can be used in localization without additional cost, since most computers today are capable of this wireless communication.

There have been researches on RSSI-based localization in logistic applications to track products, assets or equipments. For example, in [19], the RSSI is used in multilateration scheme in wireless sensor network in food transportation. Also, the paper [20] 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 [8] 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 [21], where it applies the particle filter as a localization algorithm to track a pedestrian with foot-mounted IMUs and uses RSSI from WiFi access points to compensate the drift error from an IMU. The paper also uses the precise model of the map to constraint or narrow down the possibility of the pedestrian location. Another key important idea is that the way to detect when the pedestrian stop walking and then velocity is reseted in both longitudinal and lateral directions to reduce drift error.

The RSSI-based localization that uses the robust extended Kalman filter (EKF) can be found in [10], [11]. 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 in indoor environment. 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 information with low sampling rate and high quantization noise.

In this work, we study the possibility of using sensor fusion from a low cost IMU and RSSIs by using the EKF for mobile unit localization in two-dimensional plane. The information from an IMU—we use velocity in this study— 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 discuss the characteristic of the measurement equations from both sensors. In section III, we briefly present the well known EKF 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

A. Kinematic Model

To simplify the sensor fusion scheme, the kinematic model of the vehicle, i.e., position and velocity will be used. Now, let p^x, p^y, v^x, v^y denote position and velocity in x and y direction in Cartesian space respectively. Then, let $x = \begin{bmatrix} p^x & p^y & v^x & v^y \end{bmatrix}^T$. In this note, we consider the control signal as unknown command or acceleration denoted by u. Note that, the acceleration in current velocity direction could be regarded as uncertainty to the system model. 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 a sampling time. The goal is to estimate the position of above mobile platform from IMU and RSSI sensing systems.

B. IMU Measurement Model

The IMU using in this work is low-cost microcomputer embedded system—around US$100 — composing of three-axis accelerometers, rate gyro and magnetic compass sensor that provides many outputs including the raw data from accelerometers, gyroscopes and magnetometer, as well as processed output including linear velocity and attitude. In our study, however, we consider 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 an alignment angle between any reference frame and IMU frame referencing to the magnetic north pole with positive angle measuring in clockwise direction, b^x and b^y are bias noises, and v_k^i is a general measurement noise.

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

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

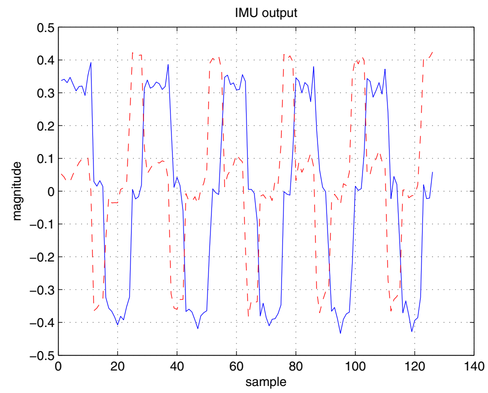


Fig. 1. Output (velocity) from IMU in both directions.

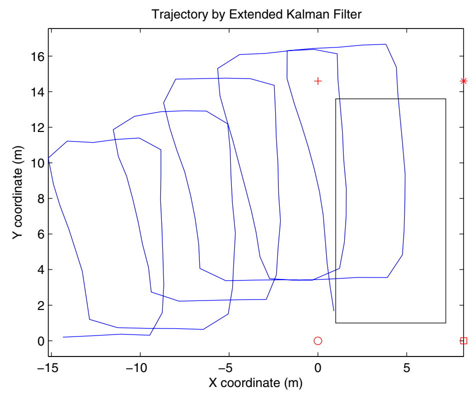


Fig. 2. Reconstructed map from IMU output only.

where w_k could be considered as uncertainties or disturbances to the system—in particular disturbs 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 new measurement from the IMU can be rewritten by

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

From our experiment, it is obvious that even a tiny bias in IMU, as in figure 1, makes a significant drift in position as depicted in figure 2. Note that, figure 2 is the result of the Kalman filter that is solely based on the IMU data.

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 ([14], [18])

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

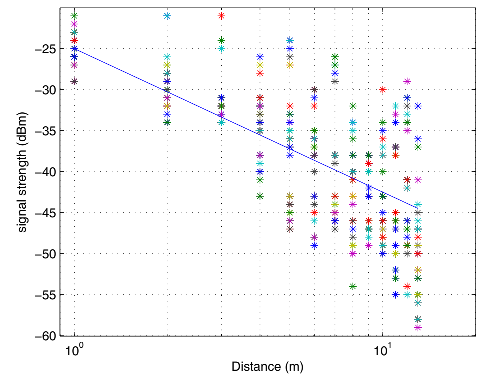


Fig. 3. Example of RSSI versus distances; solid line is approximate model: $Pr = -25 - 35\log_{10}(d)$.

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 [11], [14]. In above equation, two major factors, that make it very difficult to derive distance d, are the path loss exponent and shadowing fading. The path loss exponent γ—in the open space $\gamma = 2$—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 [14] or Table 4.2 in [13]. 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 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 with multiple references. Let (p_i^x, p_i^y) denote the position of the ith reference. Then we can define the measurement equations from RSSI, for $i = 1, 2, \ldots$, related to our system as

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

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

III. Extended Kalman Filter

In this section, since the EKF is well known (e.g., see [1], [12]), and widely used as a linearized version of the Kalman filter for nonlinear system, we, therefore, briefly give some details of it. Consider a general nonlinear system:

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

where w_k and ν_k are the process and measurement noises respectively. These noises are assumed to be white Gaussian noise with known covariance as $\mathrm{E}[w_k \cdot w_k^T] = Q_k$

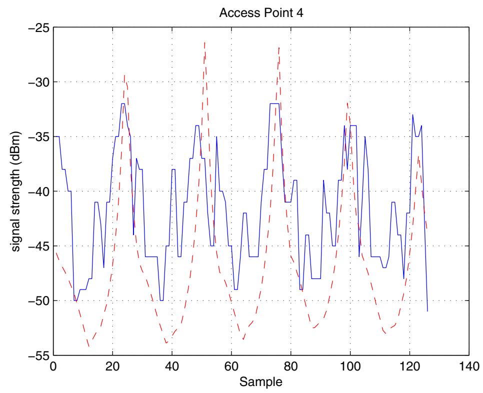


Fig. 4. RSSI from one of reference access point during experiment (solid line) comparing to ideal one (dash line) inheriting from known reference moving path.

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. Also, since the existence of the solution of the EKF is not guaranteed, Q and R weighting matrices also serve as tuning parameters for stability of the filter. In addition, we assume that $\mathrm{E}\left[x_0\right] = \eta$ and $\mathrm{E}\left[(x_0 - \eta)(x_0 - \eta)^T\right] = \Xi$. Then, the EKF could be summed up as follows:

$$
\begin{aligned}
\hat{x}_{k+1}^- &= \mathcal{F}_k\left(\hat{x}_k, u_k, k\right);\\
\hat{y}_{k+1} &= \mathcal{H}_{k+1}\left(\hat{x}_{k+1}^-\right);\\
\hat{x}_{k+1} &= \hat{x}_{k+1}^- + K_{k+1}\left(y_{k+1} - \hat{y}_{k+1}\right);\\
P_{k+1}^- &= F_k P_k F_k^T + Q_k;\\
K_{k+1} &= P_{k+1}^- H_{k+1}^T\left(H_{k+1} P_{k+1}^- H_{k+1}^T + R_{k+1}\right)^{-1};\\
P_{k+1} &= \left(I - K_{k+1} H_{k+1}\right) P_{k+1}^-,
\end{aligned} \tag{8}
$$

with initial conditions $\hat{x}_0 = \eta$ and $P_0 = \Xi$, and where F_k and H_k are the Jacobian matrices, i.e.,

$$
F_k = \frac{\partial \mathcal{F}}{\partial x}\bigg|_{x=\hat{x}_k^-},\; H_k = \frac{\partial \mathcal{H}}{\partial x}\bigg|_{x=\hat{x}_k^-}.
$$

IV. Experimental Results

In our experiment, we manually move the wheel mobile platform equipped with the IMU sensor, the WLAN receiver that communicates to four access points, and reports all the RSSIs. The IMU—as shown in the figure 5— 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 computed by microcontroller from the IMU raw data with equations suggested in the product manual. The wireless communication is the IEEE802.11b standard with 2.4GHz carrier frequency with access point model Aolynk WAP500ag as shown in figure 6.

The experiment is conducted by moving the mobile platform in the predefine rectangular path for five rounds. The EKF

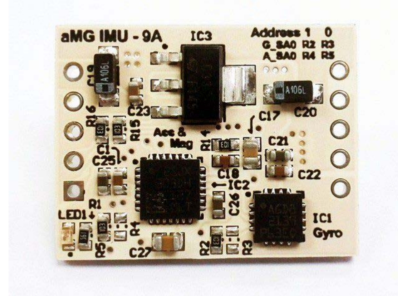


Fig. 5. IMU sensor module using in the experiment.

Fig. 6. IEEE802.11b wireless access point.

in (8) 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

$$
\mathcal{H}_k = \begin{bmatrix}
-\hat{x}_3 \sin\theta + \hat{x}_4 \cos\theta + \hat{x}_5\\
\hat{x}_3 \cos\theta + \hat{x}_4 \sin\theta + \hat{x}_6\\
-24 - 25\log_{10}(\sqrt{\hat{x}_1^2 + \hat{x}_2^2})\\
-33 - 25\log_{10}(\sqrt{\hat{x}_1^2 + (\hat{x}_2 - 14.6)^2})\\
-33 - 25\log_{10}(\sqrt{(\hat{x}_1 - 8.2)^2 + (\hat{x}_2 - 14.6)^2}\\
-24 - 25\log_{10}(\sqrt{(\hat{x}_1 - 8.2)^2 + \hat{x}_2^2}))
\end{bmatrix},
$$

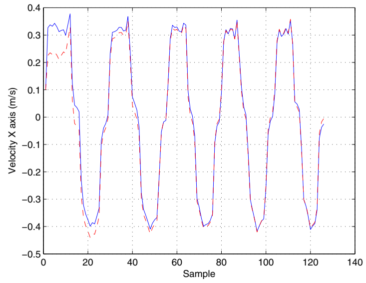
where $\theta = 0.1$ rad. The EKF parameters is of follows:

$$
Q = \begin{bmatrix}
10^{-3} & 0 & 0 & 0 & 0 & 0\\
0 & 10^{-3} & 0 & 0 & 0 & 0\\
0 & 0 & 10^{-4} & 0 & 0 & 0\\
0 & 0 & 0 & 10^{-4} & 0 & 0\\
0 & 0 & 0 & 0 & 10^{9} & 0\\
0 & 0 & 0 & 0 & 0 & 10^{-9}
\end{bmatrix},
$$

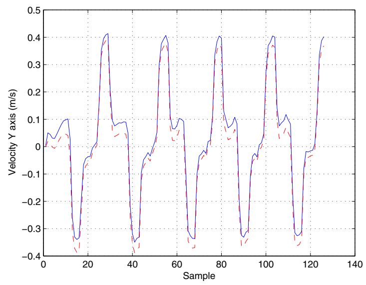
$$
R = \begin{bmatrix}
10^{-4} & 0 & 0 & 0 & 0 & 0\\
0 & 10^{-4} & 0 & 0 & 0 & 0\\
0 & 0 & 40 & 0 & 0 & 0\\
0 & 0 & 0 & 40 & 0 & 0\\
0 & 0 & 0 & 0 & 40 & 0\\
0 & 0 & 0 & 0 & 0 & 40
\end{bmatrix},
$$

$\hat{x}_0 = \begin{bmatrix}1 & 1 & 0 & 0.1 & 0 & 0\end{bmatrix}^T$ and $P_0 = 10^{-3} I_{6\times 6}$. The experimental data from IMU is shown in figure 1, and the comparison to the output from the EKF is shown in figure 7. Also, the comparisons of actual RSSIs from four access points and the estimate from EKF are depicted in figure 8.

The estimate position in x-y coordinate from EKF is plotted together with the reference moving path in figure 9. Also, the

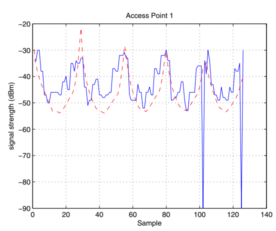


(a) x-direction

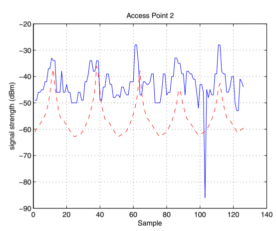


(b) y-direction

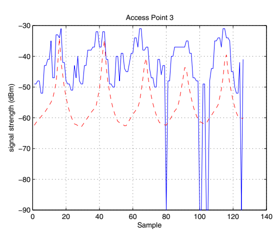
Fig. 7. Estimated and actual IMU output comparison: solid line and dash line are actual and estimate IMU output respectively.



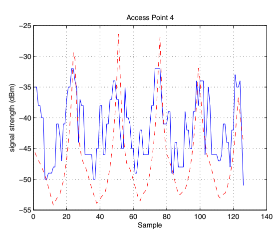
(a) access point no.1



(b) access point no.2



(c) access point no.3



(d) access point no.4

Fig. 8. Estimated and actual RSSI output comparison: solid line and dash line are actual and estimate RSSI output respectively.

absolute error in both x and y direction is shown in figure 10, and the root mean square errors (RMS) are 0.86 meter in x direction and 1.15 meter in y direction.

The bias states in both directions are shown in figure 11, and the trace of error covariance (P) is depicted in figure 12. Note that, the covariance matrix P is normally used to indicate the convergent of the filter, and, hence, it is useful in the tuning process.

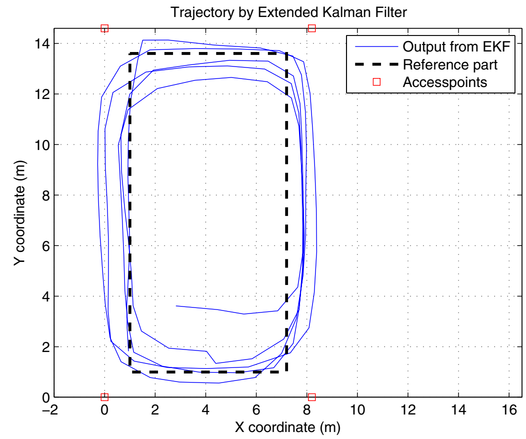


Fig. 9. Reconstructed map from the result of RSSI/IMU sensor fusion.

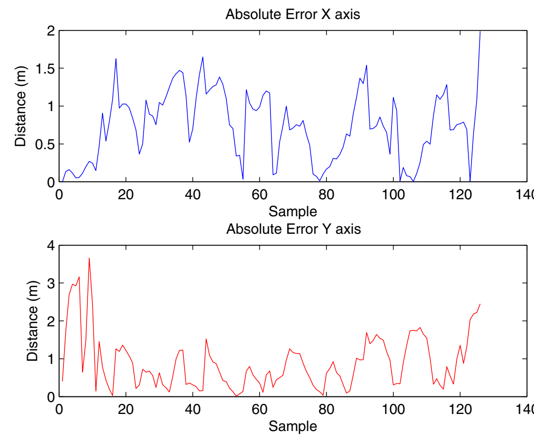


Fig. 10. Absolute error in both x and y directions.

V. Conclusions

This paper presents the study of using RSSI/IMU sensor fusion for localization problem of a mobile unit. The information from both sensors corrupted by noise and uncertainties are fused by the EKF. 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 measurement. The EKF, however, need some parameter tuning especially process and measurement noise covariances $Q,\ R$. For the future work, we will work on the method to calibrate some parameters in measurement, such as P_0, γ autonomously. Also, the fusion algorithm could be improved by some adaptive schemes for adjusting process and measurement noise covariance, or applying other estimation methods such as unscented Kalman filter.

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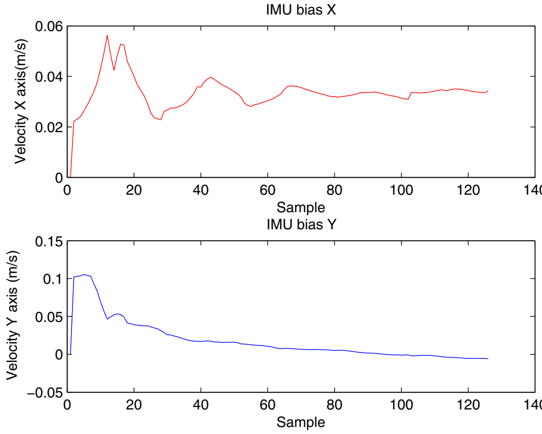

Fig. 11. IMU bias state in both x and y directions.

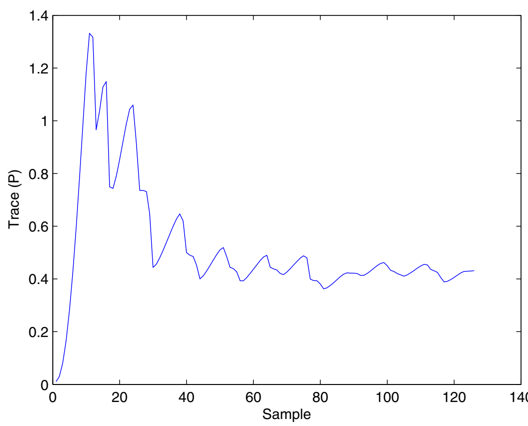

Fig. 12. The trace of error covariance (trace(P_k)).

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