An Integrated IMU and UWB Sensor Based Indoor Positioning System

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Abstract — This paper describes an Indoor Positioning System (IPS) that fuses an Ultra-Wideband (UWB) sensor-based positioning solution with an Inertial Measurement Unit (IMU) sensor-based positioning solution to obtain a robust, yet, optimal positioning performance. Sensor fusion is accomplished via an Extended Kalman Filter (EKF) design which simultaneously estimates the IMU sensors’ systematic errors and corrects the positioning errors. Fault detection, identification, and isolation are built into the EKF design to prevent the corrupted UWB sensor measurement data due to obstructions, multi-path and other interferences from degrading the positioning performance. General formulation of an IPS using IMU for both pure inertial and Kalman filter aided modes of operation using UWB sensor data is given in the paper for tracking a six degree-of-freedom (DOF) platform motion. The derivations of an 8-state EKF design are detailed in the paper for a 3 DOF (two translational and one angular motions) platform planar motion, where data from a 9-axis Motion Tracking device, MPU-9250, and four UWB radio sensor devices, DWM1000, are used. A Matlab-based simulation model is developed and built to assess the proposed IPS performance along with their performance sensitivities to platform motion profiles, UWB/inertial sensor errors, and filter update rates. With specific motion profiles, computer simulation results indicate that more than 100% positioning performance improvement over the UWB sensor-based positioning solution along can be obtained through the proposed sensor fusion solution. A laboratory test bed for a 3 DOF motion platform is designed, built, and tested to validate the proposed IPS performance. The IPS performance obtained from actual laboratory tests correlated very well with the simulation results.

Keywords—Indoor positioning system, data fusion, Extended Kalman filter, UWB, IMU

I. INTRODUCTION

Survey, given in references [1-2], lists all the known existing indoor navigation/positioning technologies. Among them are: inertial navigation, ultra-wideband, camera, infrared, sound, radar, and other electro-wave technologies. Each technology has its own unique capability and limitation if used separately. However, those limitations can be removed or minimized, and their performance accuracy and capabilities can be greatly enhanced if we fuse or combine various technologies accordingly.

Inertial navigation is a self-contained navigation technique using measurements provided by Inertial Measurement Units (IMU), mainly, accelerometers and gyroscopes, for navigation and positioning. Using the measurements from the IMU, the Inertial Navigation System (INS) can calculate the current attitude (or orientation), velocity, and position of the system starting from some known initial point. However, due to their long term drifts such as gyro/accelerometer biases and scale factor errors, the errors from the computed navigation states (position, velocity, and attitude) will grow as time grows.

Ultra-Wideband (UWB) is a radio technology transmitting signals over multiple bands of frequencies (3.1 GHz – 10.6 GHz) simultaneously with several hundred MHz of bandwidth (greater than 500 MHz), which is fundamentally different from the currently widely used, traditional radio technology. It is designed for Indoor Positioning Systems (IPSs) to overcome many challenges such as severe multipath propagation due to signal reflection from wall and furniture, Non-Line-of-Sight (NLOS) propagation due to blockages, and high attenuation and signal scattering due to greater density of obstacles. By precisely measuring the Time-of-Flight (TOF) between the transmitter, UWB radio sensor-mounted platform, and each of the receivers, UWB radio sensor-mounted anchors with known locations, their corresponding ranges can be computed. With the computed ranges, the platform position can be determined using various positioning schemes [3-5]. Since 2010, several UWB radio sensor-based positioning devices, such as DWM1000 from DecaWave [6] and Pozyx from Kickstarter, have become commercially available. Currently, several UWB radio sensor-based IPSs have been deployed in the fields [7] providing centimeter level accuracy (15 cm for Ubisense System, 30 cm for Zebra System).

Although UWB radio technology has been identified as an ideal candidate to provide precision positioning information in indoor environments, however, it still remains a challenge for the UWB-based IPS being able to continuously produce a reliable and accurate positioning information due to direct LOS multipath propagation and NLOS propagation. To overcome multipath effects, an easy way would be to remove the obstacles that may introduce those inferences or to put the receivers in a more open area. Unfortunately, this option may not be plausible in most indoor scenarios. On the other hand, the IMU-based INSs are insensitive to these interferences.

One particular interest is to fuse the above two technologies: inertial navigation technology and UWB radio technology for IPS applications because these two technologies are complimentary to each other. The idea of using sensor fusions for the IPSs have been reported in [8-11]. An IPS with region-based fingerprinting approach integrated with the inertial sensing was presented in [8] for tracking objects in piecewise constant velocity motion in Wi-Fi wireless networks. In [9], a Kalman filter was chosen to fuse the data coming from all sensors, mainly, the Wi-Fi fingerprinting engine, accelerometers, and compass. Similarly, in [10], authors
presented the idea of fusing all the available data obtained from built-in sensors in an Android smartphone. The fusion algorithm given in [10] is quite complicated and ad hoc. A sensor fusion of a RSSI (Received Signal Strength Indicator)-based radio positioning system with an INS was described in [11] where the INS, a stand-alone system, provides independent INS positioning solutions to the RSSI-based positioning solutions. The applications of this sensor fusion idea for indoor pedestrian navigation systems were also reported in [12-13] where foot mounted inertial pedestrian navigation systems are augmented with a UWB-based Wireless Sensor Networks (WSNs).

In the proposed sensor fusion IPS architecture, we use UWB radio sensor data to calibrate the inertial sensors’ long term drifts and correct the platform position errors while UWB radio sensor signals are available and reliable, and then switch to the computed navigation states obtained from calibrated inertial sensors when UWB radio sensors are not available or become unreliable. This sensor fusion is accomplished through the use of an Extended Kalman Filter (EKF), a tightly coupled filter, which calibrates the inertial sensor systematic errors using the measured ranges from UWB-based radio sensors and, at the same time, provides position corrects for data fusion. With this proposed system, an accurate indoor positioning and navigation can be continuously provided without degradation.

In this paper, a novel IPS with a sensor fusion of an IMU-based positioning solution and an UWB-based positioning solution is described. In Session II we brief the proposed sensor fusion IPS architecture, major signal processing, and algorithms for a general 6-DOF platform motion tracking. Session III details the derivations of an 8-state EKF for a 3-DOF platform planar motion tracking. A Matlab-based simulation model is then described in Session IV to assess the EKF-based sensor fusion performance and their performance sensitivities to many design parameters. A laboratory test bed designed and built for the proposed IPS tracking a 3-DOF platform motion is described in Session V along with their experiment results. Finally, conclusions are drawn in Session VI.

II. INTEGRATED IMU-BASED AND UWB- BASED INDOOR POSITIONING SYSTEM

Fig. 1 shows the proposed integrated IMU and UWB sensor based indoor positioning system, where three orthogonal accelerometers, three orthogonal gyros, one UWB radio sensor (labeled as Tag radio sensor) are mounted on the platform body (B frame), and four UWB radio sensors (labeled as Anchor radio sensors - three are required and the fourth one is for redundancy) are placed within the building with known locations. The three orthogonal gyros are assumed to be aligned with the three accelerometers.

A. IMU Sensor-based Positioning Processing

The platform motion in terms of their position and velocity with respect to an indoor positioning coordinate frame, denoted as E frame, can be obtained as follows by performing double integrations of three computed accelerations, \(a_{mx}, a_{my}, a_{mz}\) expressed in a local Navigation coordinate frame (N frame):

\[
\begin{align*}
\dot{x}_p(t) &= x_p(t_0) + \int_{t_0}^{t} v_p^N(\tau) d\tau \\
\dot{y}_p(t) &= y_p(t_0) + \int_{t_0}^{t} v_p^N(\tau) d\tau \\
\dot{z}_p(t) &= z_p(t_0) + \int_{t_0}^{t} v_p^N(\tau) d\tau
\end{align*}
\]  

(1)

\[
\begin{align*}
\dot{x}_p^N(t) &= x_p(t_0) + \int_{t_0}^{t} v_p^N(\tau) d\tau \\
\dot{y}_p^N(t) &= y_p(t_0) + \int_{t_0}^{t} v_p^N(\tau) d\tau \\
\dot{z}_p^N(t) &= z_p(t_0) + \int_{t_0}^{t} v_p^N(\tau) d\tau
\end{align*}
\]  

(2)

Where \(\dot{x}_p(t_0), \dot{y}_p(t_0), \dot{z}_p(t_0)\) are the initial platform position and \(\dot{x}_p^N(t_0), \dot{y}_p^N(t_0), \dot{z}_p^N(t_0)\) are the initial platform velocity with respect to E frame. The equations for computing the three accelerations, \(a_{mx}^N, a_{my}^N, a_{mz}^N\) are given by the following inertial navigation equations [14] in a rotating frame:

\[
a_n^N = \begin{bmatrix} a_{mx}^N \\ a_{my}^N \\ a_{mz}^N \end{bmatrix} = \begin{bmatrix} \hat{C}_B^N \\ \hat{C}_B^N \\ \hat{C}_B^N \end{bmatrix} \begin{bmatrix} a_B^N \\ a_B^N \\ a_B^N \end{bmatrix} - \hat{\omega}_{nB}^N \times \hat{V}_m^N + \mathbf{g}_N
\]  

(3)

Where the Coriolis force (a vector cross of an angular velocity vector and a platform translation velocity vector) is included in the above equations with \(a_{mx}^N, a_{my}^N, a_{mz}^N\), three measured platform body accelerations, \(\mathbf{g}_N\), a known gravity vector, \(\hat{\omega}_{nB}^N\), the angular velocity vector (representing the platform transport rate vector expressed in N frame), \(\hat{V}_m^N = [\hat{v}_{xp}^N \hat{v}_{yp}^N \hat{v}_{zp}^N]^{T}\), the computed platform translational velocity vector, and \(\hat{C}_B^N\), a 3×3 direction cosine matrix, which can be computed from three measured gyro outputs: \((\omega_{mx}, \omega_{my}, \omega_{mz})\) and a 3×3 direction cosine matrix, \(C_j^N\) representing the attitude of Earth-Center-Inertial frame (I frame) with respect to N frame:

\[
\hat{C}_B^N = C_j^N \begin{bmatrix} C_j^N \end{bmatrix}
\]  

(4)

\[
\hat{C}_B^{\dot{z}} = \hat{C}_B^N \begin{bmatrix} \dot{C}_j^N \end{bmatrix} x
\]  

(5)
In the above equations, $\omega_z$ is the earth rate, (lat, long) are the latitude and longitude of the motion platform. Fig. 2 shows the corresponding data flow for the IMU sensor-based positioning processing.

B. UWB Sensor-based Positioning Processing

The UWB sensor-based positioning processing is comprised of two parts: (1) to compute the four range signals, the distances between the transmitter (the tag radio sensor) and the four receivers (the four anchor radio sensors), using the measured Time of Flight (TOF), and (2) to determine the platform position using the four computed range signals.

Fig. 3 shows the time of arrival propagation diagram, where $T_1$ is the time difference between the time when the tag radio sensor sent the signal to each of the anchor sensors and the time when the tag radio sensor received the signal from each of the anchor radio sensors, and $T_2$ is the time difference between the time when each of the anchor radio sensors received the signal from tag radio sensor and the time when it is ready to send the signal back to the tag radio sensor. Using the received $T_2$ from each of the anchor radio sensors, the tag radio sensor can then compute the corresponding distance between them:

$$\text{TOF} = \frac{T_1 - T_2}{2}$$

$$\text{Distance} = r = C \times \text{TOF} \quad C = 3 \times 10^8 \text{ m/s}$$

With the four computed ranges, $r_i$ the platform position can be determined using either trilateration method \[3\] or least-squared method \[4-5\]. The position solution using the direct least-squared method is given by:

$$\hat{x} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix} = [H]^{-1}z$$

where

$$H = \begin{bmatrix} (x_1 - x_t) & (y_1 - y_t) & (z_1 - z_t) \\ (x_2 - x_t) & (y_2 - y_t) & (z_2 - z_t) \\ (x_3 - x_t) & (y_3 - y_t) & (z_3 - z_t) \end{bmatrix}$$

$$z = \begin{bmatrix} r_1^2 - \hat{r}_1^2 \\ r_2^2 - \hat{r}_2^2 \\ r_3^2 - \hat{r}_3^2 \end{bmatrix}$$

If only three UWB anchor radio sensors are available, one can use the following iterative decent (least-squared) method:

1. At step $i$, compute the current range estimates based on the currently computed platform position:

$$\hat{r}_i(i) = \sqrt{(\hat{x} - x_t)^2 + (\hat{y} - y_t)^2 + (\hat{z} - z_t)^2}$$

2. Compute the measurement error vector and the gradient matrix, $H(i)$:

$$\Delta r(i) = \begin{bmatrix} r_1 - \hat{r}_1(i) \\ r_2 - \hat{r}_2(i) \\ r_3 - \hat{r}_3(i) \end{bmatrix}$$

$$H(i) = \begin{bmatrix} (x_1 - x_t) & (y_1 - y_t) & (z_1 - z_t) \\ (x_2 - x_t) & (y_2 - y_t) & (z_2 - z_t) \\ (x_3 - x_t) & (y_3 - y_t) & (z_3 - z_t) \end{bmatrix}$$
(3) Update the platform position estimates:
\[
\begin{bmatrix}
\hat{x}_i \\
\hat{y}_i \\
\hat{z}_i \\
\end{bmatrix} \leftarrow \begin{bmatrix}
\hat{x}_i \\
\hat{y}_i \\
\hat{z}_i \\
\end{bmatrix} + H'(i)H(i)^{-1}H'(i)\Delta r(i) \tag{22}
\]

(4) Repeat step #1 until the norm of measurement error vector, \(\|\Delta r(i)\|\) less than a small positive value \(\varepsilon\).

C. Sensor Fusion Positioning Processing

In principle, by using the measurements from inertial sensors and equations 1 through 10, one can determine platform current position and velocity continuously starting from some known initial point without external aids. However, due to inertial sensors’ long term drifts such as biases and scale factor errors, the errors obtained from the computed navigation states (position, velocity, and attitude) will grow over time. Although the UWB sensor-based positioning solution as described in Session II (B), on the other hand, does not exhibit the problem of positioning error growth. However, due to obstructions, multi-path and other interferences to the received signals, the corrupted UWB sensor data can result in large determination errors from time to time, which could severely degrade platform positioning accuracy performance.

To overcome each individual shortfalls of the above two positioning solutions, we implement an Extended Kalman Filter (EKF) that combines or fuses the two positioning solutions in such a way that the UWB sensor-based positioning solution is used to calibrate or estimate the IMU errors and the IMU sensor based positioning solution is used to detect and isolate the corrupted UWB sensor data to improve the overall positioning performance accuracy.

In the EKF design, (1) we define the state variables consisting of platform three position errors, three velocity errors, three attitude errors, and the necessary state variables (up to 21 state variables) characterizing IMU sensor errors such as accelerometers’ biases, scale factor errors, misalignment errors and gyros’ biases, scale factor errors, misalignment errors; (2) using the perturbation method, we derive the linearized dynamic equations based on Equations 1 through 10 for the defined state variables; and (3) we construct the measurement equations (range measurements from each UWB anchor radio sensors) as functions of the defined state variables. In state-space format, the derived error dynamic equations and measurement equations can be expressed as:

\[
\dot{x} = [F(t)]x + \eta \tag{23}
\]

\[
z = g(x) + n \tag{24}
\]

Based on Equations 23 and 24, a discrete EKF can be implemented as shown in the following data flow where inputs (range measurements) from four UWB sensors and current platform navigation states from IMU sensor-based positioning solution are combined (or fused) to produce the updated platform position/velocity estimates and inertial sensor error corrections, which are used in the IMU sensor-based positioning solution processing:

Fig. 4. Sensor Fusion Processing Data Flow

The details can better be described in the following session where platform is constraint to a level plane with only 3 DOF motion.

III. DERIVATIONS OF 8-STATE EKF FOR PLANAR PLATFORM POSITIONING

Let’s consider a simple 2-dimentional positioning for a platform, which moves on an x-y plane with a body-mounted IMU and an UWB tag sensor as illustrated in Fig 5. The two orthogonal accelerometers, one along x-axis, and one along y-axis measuring the platform body accelerations in both x and y directions with respect to pseudo inertial frame – non-moving E frame. One gyro along z-axis measuring body angular velocity with respect to I frame. Four UWB anchor radio sensors with known locations mounted on the building ceiling along with the body mounted UWB tag radio sensor provide four range measurements, r1, r2, r3, and r4.

For mathematical simplicity purpose, we assume that the inertial sensors contain only the biases’ errors. By defining the following state variables or error signals:

\[
\begin{align*}
\Delta x_p &= x_p - \hat{x}_p \\
\Delta y_p &= y_p - \hat{y}_p \\
\Delta b_x &= b_x - \hat{b}_x \\
\Delta b_y &= b_y - \hat{b}_y \\
\Delta b_z &= b_z - \hat{b}_z \\
\Delta \theta &= \theta - \hat{\theta} \\
\end{align*}
\]

and applying small signal perturbations to Equations 1 through 10, one obtains the following dynamic equations, in state-space format, for the defined state variables:
\[
\begin{aligned}
\mathbf{x}_2 &= \begin{bmatrix}
\dot{x}_1 \\
\dot{x}_2 \\
\dot{x}_3 \\
\dot{x}_4 \\
\dot{x}_5 \\
\dot{x}_6 
dashend{bmatrix} = 
\begin{bmatrix}
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -\cos(\psi) & 0 & -\omega_{\text{ang}} & \sin(\psi) & f_{\text{acc}} & \hat{\psi}_p \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 
dashend{bmatrix} \begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
x_6 
dashend{bmatrix} + 
\begin{bmatrix}
0 \\
\eta_2 \\
\eta_3 \\
\eta_4 \\
\eta_5 \\
\eta_6 
dashend{bmatrix}
\end{aligned}

= F(t) \mathbf{x}_1 + \mathbf{\eta}
\]

where

\[
\begin{aligned}
f_{27} &= -\left[ (\sin(\psi))\hat{a}_{\text{com}}^g + (\cos(\psi))\hat{a}_{\text{com}}^n \right] \\
f_{27} &= \left[ (\cos(\psi))\hat{a}_{\text{com}}^g - (\sin(\psi))\hat{a}_{\text{com}}^n \right] \\
\eta_2 &= -\left[ (\cos(\psi))n_{\text{com}} + (\sin(\psi))n_{\text{com}} + \hat{\psi}_p n_{\text{ang}} \right] \\
\eta_3 &= -\left[ (\sin(\psi))n_{\text{com}} - (\cos(\psi))n_{\text{com}} - \omega_{\text{ang}} \hat{\psi}_p \right] \\
\hat{a}_{\text{com}}^g &= \hat{a}_{\text{com}}^g - \dot{\hat{b}} \\
\hat{a}_{\text{com}}^n &= \hat{a}_{\text{com}}^n - \dot{\hat{b}} \\
\hat{\hat{a}}_{\text{com}}^n &= \hat{a}_{\text{com}}^n - \hat{\hat{b}} \\
\hat{\psi}_p &= \int_0^\tau \hat{\psi}_p(\tau) d\tau; \hat{x}_p = \int_0^\tau \hat{\psi}_p(\tau) d\tau \\
\hat{\psi}_p &= \int_0^\tau \hat{\psi}_p(\tau) d\tau; \hat{\psi}_p = \int_0^\tau \hat{\psi}_p(\tau) d\tau \\
\hat{\psi} &= \int_0^\tau \hat{\psi}_p(\tau) d\tau
\end{aligned}
\]

Then the innovation process signals, defined as \( \mathbf{\mu}(t) = \mathbf{z}_n (t) - \hat{\mathbf{z}}_m (t) \), can be approximated by:

\[
\begin{aligned}
\mathbf{\mu} &= \begin{bmatrix}
\frac{\partial R_m}{\partial x_p} & 0 & 0 & 0 & 0 \\
\frac{\partial R_m}{\partial y_p} & 0 & 0 & 0 & 0 \\
\frac{\partial R_m}{\partial \hat{x}_p} & 0 & 0 & 0 & 0 \\
\frac{\partial R_m}{\partial \hat{y}_p} & 0 & 0 & 0 & 0 \\
\frac{\partial R_m}{\partial \hat{\psi}_p} & 0 & 0 & 0 & 0 \\
\frac{\partial R_m}{\partial \hat{\psi}_p} & 0 & 0 & 0 & 0 
dashend{bmatrix} \mathbf{x}_c + \mathbf{n} 
\end{aligned}
\]

Based on Equations 26 and 29, one can then implement the discrete EKF as shown in Fig. 4.

One can use the innovation process signals to reject bad UWB sensor measurements due to multipath propagation or other interferences. One simple way is to compute the absolute values of innovation process signals \( \mathbf{\mu}(t) \) or \( |\mathbf{\mu}(t)| \), and compare them to a pre-set threshold value, said, C. If \( |\mathbf{\mu}(t)| > C \) for all i, then one can disable the Kalman filter update by setting the Kalman filter gain matrix equal to zeros matrix, skipping the error covariance matrix update, and proceeding to the next Kalman filter update cycle, otherwise, proceed with the regular Kalman filter update cycle. It is noted that one can still process the good UWB sensor measurement data (for those with \( |\mathbf{\mu}(t)| \leq C \)) with reduced number of measurement equations in Equation 29. In general, the threshold value C shall be greater than 3 sigma value of radio sensor measurement error, which is equal to 3*10cm = 30cm, and less than 6 sigma value of radio sensor measurement error, which is equal to 6*10cm = 60cm. It is also notice that we in general don't perform this threshold test at the beginning when Kalman filter is still in the transient period.

IV. MATLAB SIMULATIONS AND RESULTS

To assess the proposed EKF and sensor fusion positioning performance, a Matlab-based simulation model as shown in Fig. 6 was built to model: (1) the platform motion, (2) inertial sensors’ errors, (3) range measurements from four UWB sensors, and (4) discrete EKF. Table I gives the parameters and initial conditions used in the simulations.

Three different motion profiles: straight motion, circular motion, and track motion as shown in Fig. 7 were generated to evaluate EKF performance and platform positioning accuracy.
TABLE I. PARAMETERS AND INITIAL CONDITIONS USED IN THE SIMULATIONS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
<th>Units</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerometer</td>
<td>100Hz sampling rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bx(0)</td>
<td>0.1 g</td>
<td></td>
<td>Initial accel bias (x-axis)</td>
</tr>
<tr>
<td>by(0)</td>
<td>-0.1 g</td>
<td></td>
<td>Initial accel bias (y-axis)</td>
</tr>
<tr>
<td>0.01 g</td>
<td></td>
<td></td>
<td>Accel noise 1st (x-axis)</td>
</tr>
<tr>
<td>0.01 g</td>
<td></td>
<td></td>
<td>Accel noise 1st (y-axis)</td>
</tr>
<tr>
<td>0.01/3600 g/sqrt(sec)</td>
<td>x accel bias stability 1σ</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.01/3600 g/sqrt(sec)</td>
<td>y accel bias stability 1σ</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gyro</td>
<td>100Hz sampling rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bz(0)</td>
<td>0.5 deg/sec</td>
<td></td>
<td>Initial gyro bias</td>
</tr>
<tr>
<td>0.02 deg/sec</td>
<td></td>
<td></td>
<td>Gyro noise (or angle random walk) 1σ</td>
</tr>
<tr>
<td>0.02/3600 deg/sec</td>
<td>Gyro rate random walk 1σ</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UWB sensor</td>
<td>10Hz sampling rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.1 Meter</td>
<td></td>
<td></td>
<td>1σ</td>
</tr>
<tr>
<td>Initial conditions</td>
<td>Value</td>
<td>Units</td>
<td>Comments</td>
</tr>
<tr>
<td>bx_hat(0)</td>
<td>0 g</td>
<td></td>
<td></td>
</tr>
<tr>
<td>by_hat(0)</td>
<td>0 g</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bz_hat(0)</td>
<td>0 deg/sec</td>
<td></td>
<td></td>
</tr>
<tr>
<td>psi_hat(0)</td>
<td>0.5 deg/sec</td>
<td></td>
<td>1σ (Monte Carlo runs)</td>
</tr>
</tbody>
</table>

Given one particular sample run, Fig. 8 depicts the time responses of inertial sensor bias estimate errors and angle error for the three platform motion profiles. Table II summaries the EKF and sensor fusion positioning solution performance based on 100 Monte Carlo runs. The preliminary results indicate that: (1) the straight motion profile provides the best performance among the three, and (2) better than 40% positioning accuracy improvement over the UWB sensor-based positioning solution along can be achieved using the proposed sensor fusion positioning solution. Positioning performance improvement can be further realized by increasing the UWB sensor processing data rate as shown in Fig. 9. As shown, over 100% performance improvement can be obtained as filter update rate is greater than 20 Hz with the straight motion profile.

TABLE II. EKF PERFORMANCE SUMMARY AND COMPARISON

<table>
<thead>
<tr>
<th>Filter Performance Comparison - 100 Monte Carlo Runs (3σ)</th>
<th>Straight Motion</th>
<th>Circular Motion</th>
<th>Race Track Motion</th>
</tr>
</thead>
<tbody>
<tr>
<td>bx</td>
<td>0.2291</td>
<td>2.7164</td>
<td>0.6576 mg</td>
</tr>
<tr>
<td>by</td>
<td>0.1465</td>
<td>1.8392</td>
<td>2.6148 mg</td>
</tr>
<tr>
<td>bz</td>
<td>0.0056</td>
<td>0.1113</td>
<td>0.1531 degree/sec</td>
</tr>
<tr>
<td>x-position err</td>
<td>11.29</td>
<td>14.47</td>
<td>18.04 cm</td>
</tr>
<tr>
<td>y-position err</td>
<td>11.29</td>
<td>15.04</td>
<td>17.19 cm</td>
</tr>
</tbody>
</table>

V. TEST SETUP AND EXPERIMENTAL RESULTS

To validate the proposed IPS in a real indoor environment, we set up a test bed within the existing University EE Department’s laboratory room with approximately 10.45m long and 11.7m width as shown in Fig. 10. The room contains mainly tables, chairs, electronic equipment, and other furniture.

Fig. 6. Matlab-based Simulation Model Data Flow

Fig. 7. Three Platform Motion Profiles

Fig. 8. EKF Inertial Sensor Error Estimates’ Performance

Fig. 9. Platform Positioning Performance as a Function of Filter Update Rate

Fig. 10. Platform Positioning Performance as a Function of Filter Update Rate
Green marks represent the positions where the four UWB anchor sensors (4 DWM1000) are located. The platform, represented by a printed circuit bread board as shown in Fig. 11, has a MPU-9250 IMU sensor, a DWM1000 radio sensors, and a Power PC, Stm32f405 for data processing and communications. The platform is securely mounted either on a straight rail or a wheel trolley. The straight rail provides a straight motion profile with known positions for absolute references and the wheel trolley provides near square motion profiles and arbitrary routes to support the laboratory tests.

Utilizing the built-in Matlab serial port commands, we collect the platform acceleration and angular velocity data from MPU-9250 at 100 Hz and four distance measurement data computed from TOF at 50 Hz. The baud rate is 115200. The collected data are then inputted into the developed 8-state Kalman filter computation as described in Sessions 3 and 4.

In this test, we created a left-right periodical platform straight motion with an approximately 2-seconds period for 40 seconds. Fig. 12 shows the time responses of two accelerometer biases’ estimates and the gyro bias’s estimate with the 8-state EKF. Table III compares the x-axis position errors (for the last 20 seconds) among three different approaches where the $\sigma$ value is the sum of the absolute value of means and 3 times standard deviations. As shown, the positioning accuracy of the proposed data fusion approach outperforms (2.5 to 5 times) other two approaches using UWB sensors along. Fig. 13 shows the 2-dimensional x-y positioning plots over 40-seconds period – EKF (in red color) vs LS (in green color) on the left and EKF vs TRI (in blue color) on the right.

**B. Near square motion on the wheel trolley test**

In this test, a near square motion was created with the platform mounted on the wheel trolley which was moved against a square block (approximately 1.1 meters long) fixed on the ground. A laboratory equipment is situated near the square block as shown in Fig. 10. Fig. 14 shows the corresponding 4 range measurements from UWB (left plots) and 4 innovation process signals from EKF (right plots) during the 40-seconds counter-clock motion. The interferences induced range measurement errors were clearly observed when the platform is near the left side and the upper right corner of the square block. The x-y position tracking comparison between the proposed EKF approach (in blue color) and the LS approach (in green color) using UWB sensors only is shown on the left hand side of Fig. 15. The right hand side of the figure shows the tracking performance improvement by applying the threshold test ($C = 0.5$) as described in Section III.
C. Arbitrary route test

The last test was created by moving the platform mounted on wheel trolley with an arbitrary route within the laboratory space. Fig. 16 shows the x-y position tracking results of the proposed EKF approach (in blue color) applying the threshold test with $C = 0.3$ and the LS approach (in green color). The results indicate that the proposed EKF approach not only greatly reduces the tracking error but also produces much smooth motion tracking by removing detected glitches produced by UWB sensors.

VI. CONCLUSIONS

In this paper we have presented a novel IPS that fuses an UWB sensor-based positioning solution with an IMU sensor-based positioning solution to obtain a robust, yet, optimal positioning performance. We show how the sensor fusion can be accomplished via an EKF design, which simultaneously estimates the IMU sensors’ systematic errors and corrects the positioning errors. We present a general system architecture and data processing for the proposed IPS tracking a 6 DOF platform motion. We develop a Matlab-based simulation model to assess the EKF performance and their performance sensitivities to platform motion profiles, and EKF update rates. We show that, with specific motion profiles, more than 100% positioning performance improvement over the UWB sensor-based positioning solution along can be obtained through the proposed sensor fusion solution. We describe a laboratory test bed designed and built for a 3 DOF platform motion. The test bed is used to validate the proposed IPS performance. Experimental results have shown the improved positioning performance accuracy using the proposed approach and correlated very well with the simulation performance prediction results.

REFERENCES