

Accurate UWB and IMU based Indoor Localization for Autonomous Robots

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Abstract—Real-time monitoring and tracking of mobile robots in an indoor environment is very important for numerous applications. In this paper a method to accurately locate mobile robots with sensor fusion is proposed. The acceleration from an inertial measurement unit (IMU) and the 2-D coordinates received from the Ultra-Wideband(UWB) anchors are fused together in a Kalman filter to achieve an accurate location estimation. The proposed method increases robustness, scalability, and accuracy of location. The measurement results, which was obtained using the proposed fusion, show considerable improvements in accuracy of the location estimation which can be used in different Indoor Positioning System (IPS) applications requiring precision.

I. INTRODUCTION

Localization is the process of determining locations of people, equipment, and other objects. It has been a dynamic research range in which a significant part of the research concentrates on using existing technologies to address the issue of location estimation. Autonomous mobile robots have increasingly been used in a wide range of applications as suggested in [1]. Due to the increased demand for precise indoor location for robots, it has become an active research area in which different solutions have been proposed [2], [3].

Wireless Indoor Positioning Systems (IPS) have become very popular in recent years. These systems have been successfully used in many applications such as asset tracking and automated robot in inventory. Due to the influence of the building structures in indoor environments, techniques have to be further developed to cope with different issues like varying Line of Sight (LOS) and Non-Line of Sight (NLOS) or severe multipath conditions for radio based wireless technologies. Again some IPS lack in long term independent navigation since the accuracy disintegrates with time. Some sensor fusion methods, for meeting centimetre-level accuracy requirements for autonomous robots, have emerged [2], [3], [4].

This paper presents an integration of two of the most promising technologies for indoor positioning. The first one is a radio localization system based on the new wireless communication technology called Ultra-Wideband (UWB). The second is an Inertial Navigation System (INS) using an Inertial Measurement Unit (IMU). The goal of this integration is to improve the accuracy of localization for indoor autonomous robots. The measurements of these two systems are coupled in order to combine the complementary advantages of INS and UWB. This fusion is achieved through the use of a Kalman filter [5].

The Kalman filter is a widely used technique that continues to be an important filter for sensor fusion algorithms. It was designed to filter two or more linear systems with Gaussian error statistics and provide a more accurate output; for instance, using the global positioning system (GPS) and IMU for autonomous driving. However, there are many scenarios where nonlinear systems also require filtering or smoothing. As a result, the Extended Kalman Filter (EKF) and unscented Kalman filter were designed to handle nonlinear systems. This paper focuses on the use of an EKF with IMU and UWB based IPS data. The performance of the proposed solution is evaluated and compared with the performance of an UWB based IPS.

The rest of this paper is organized as follows. Section II discusses the background of indoor positioning systems, UWB, Inertial Navigation System and the Kalman Filter. Section III describes the system model and the use of the Kalman filter for the experiment. Next, Section IV briefly explains the results of the experiment. Lastly, Section V concludes this paper and discusses some future work regarding the use of IPS.

II. BACKGROUND

A. Indoor Positioning Systems

An IPS is the indoor counterpart to the GPS. The communication technology used in IPS are short-range radio, such as WiFi, UWB, RFID, ZigBee, and ultrasound. The main research approaches for IPS include infrastructure-based systems and infrastructure-free systems. Infrastructure-based systems deploy reference nodes with known locations to complete the positioning of the mobile nodes. For instance, Park et al. deployed ZigBee for an indoor location system [3]. Due to the influence of the building structures in indoor environments, the accuracy of this system is in about meters. Several approaches also employ INS-based infrastructure-free systems for indoor navigation. Evennou et al. proposed a WiFi/INS integration navigation system for indoor mobile positioning in [4]. Infrastructure based systems are more costly due to the requirement of extra specialized hardware, but also provide much better accuracy. Meanwhile, infrastructure free systems are cheaper, but are not as accurate. Currently, there is no set standard in terms of wireless spectrum for indoor positioning due to all of the various types of complex indoor environments. The best candidate for high accuracy positioning is an UWB based IPS

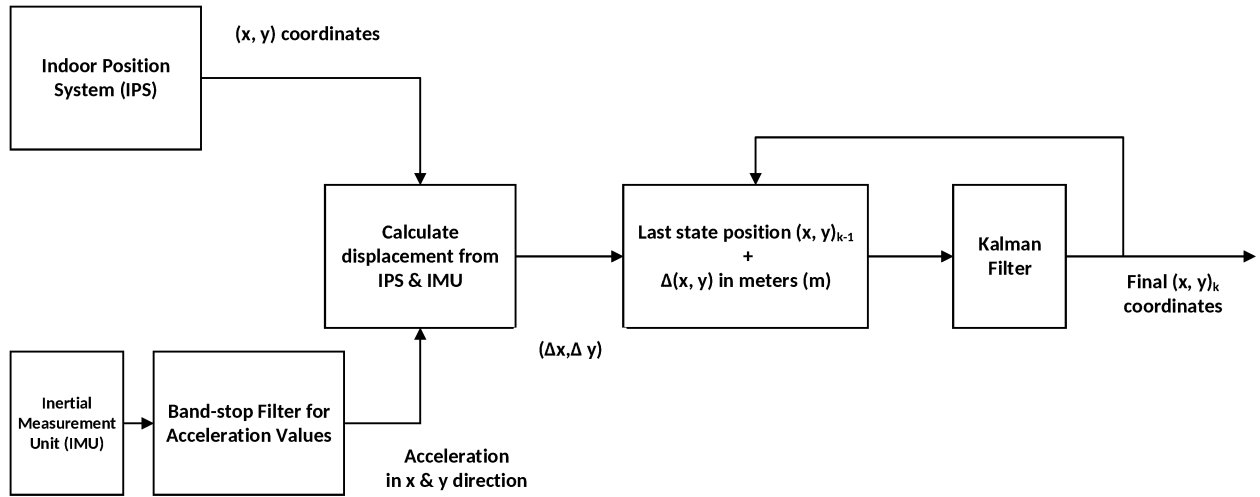


Fig. 1. An overview of the system.

since UWB does not interfere with other wireless spectrum and has accuracy on the order of centimeters.

B. Ultra-Wideband

UWB indoor positioning systems have been proposed for highly accurate solutions, where other radio frequency technologies, such as WLAN, Zigbee or Bluetooth, cannot offer those accuracy levels. For UWB positioning systems, time-based schemes namely Time of Arrival (TOA) and Time Difference of Arrival (TDOA) provide very good accuracy due to the high time resolution (large bandwidth) of UWB signals. There are proposals to use UWB for positioning on industrial wireless sensor networks [6]. Also, there are already some commercially available solutions in the industry under the framework of the Internet of Things (IoT) [7], [8], [9]. Most of the highly accurate UWB positioning systems available in literature seem to work in very controlled environments. However, under NLOS conditions, which is the common case in complex indoor environments, there is a severe loss in the positioning precision of UWB systems. A more effective way is to fuse this UWB based IPS with an INS to improve the localization of robots.

C. Inertial Navigation System

INS is based on the Newtons second law and has many advantages. The most important one is that it does not rely on external information and does not radiate any energy while operating. Therefore, it is a kind of autonomous or self-contained navigation system, which is quite suitable for any applications. INS is very accurate over short periods with high update frequency. However, the accuracy of these sensors are affected due to accumulation of noise and drift errors from accelerometers and gyroscopes. Therefore, IMU are generally fused with other positioning technologies. In these fusion schemes, IMU records are used to compensate for the lack of data continuity in the absolute position determinations. We use

a commercially available IMU, comprised of LSM303 magnetometer and accelerometer for the acceleration measurement and L3GD20 Gyroscope for angular velocity [10].

D. Kalman Filter

Kalman filtering is a great way to fuse information coming from two or more sensors with Gaussian error. Afterwards, the joint probability of the sensor error distributions can be used to estimate a more accurate value. The fusion of GPS and Simultaneous Localization and Mapping (SLAM) allow for increased robustness, increased scalability, and improved localization [11]. Accordingly, the fusion of IPS and SLAM should further improve the localization for autonomous robot applications. In areas with unreliable GPS signals, such as tunnels or underground parking garages, an IMU can be fused with the IPS and provide an improved estimate of the current position. Furthermore, a comparison of different smoothing methods tested in [12] shows that the use of a modified Kalman filter produced the smallest mean difference when comparing speed and acceleration values, proving that the Kalman filter is suitable for this application.

III. DESCRIPTION

An overview of the system is represented in Fig. 1 with the experimental parameters provided in Table I. The actual position of the robot was measured using a laser distance meter with a 95% confidence interval of (2.1737 m, 2.1815 m) and (2.1749 m, 2.1827 m). The setup for this experiment is a small office area with LOS communication between the anchors and tag as seen in Fig. 2 and was run for 45 seconds (s). The sensors used for this experiment are an IMU for the acceleration and the DECAWAVE TREK1000 evaluation kit as the IPS. The IMU is placed on a robot with the Z-axis perpendicular to the ground and an offset value for the x and y components were included to align it with the expected orientation. The sensor data is also passed through a band-stop filter to further improve its accuracy when the robot is

TABLE I
EXPERIMENT PARAMETERS

Parameter	Value
Anchor 0	(0.201 m, 3.149 m)
Anchor 1	(4.152 m, 3.148 m)
Anchor 2	(2.402 m, 0.000 m)
Actual Position (95%)	(2.1743 m, 2.1821 m)
IMU Frequency	20 Hz
IPS Frequency	0.67 Hz
Experiment time	45 s

not moving. Lastly, the data rates of the IPS and acceleration from the IMU are 0.67 Hz and 20 Hz respectively, the data outputs are (x, y) coordinates and meters per second squared (m/s^2) respectively.

The requirements to use the Kalman filter are that the sensors must have a Gaussian error distribution and the data must be compared in the same unit of measurement. Fig. 3 provides the distribution of the x coordinates obtained from the IPS. The bar chart shows the frequency count for the values received and the solid line is an approximated probability density function (pdf). Moreover, the mean of the x coordinate is 2.1737 meters (m) with a variance of 0.0044 m. The y coordinate was also observed to have a similar distribution as the x coordinate with a mean of 2.1855 m and a variance of 0.0040 m. For the IMU data, Fig. 4 provides the distribution of the acceleration in the x direction. Similarly, the histogram is the frequency count for the values received and the solid line is the approximated pdf. The mean for these IMU measurements is $3.6309 \times 10^{-5} \text{ m/s}^2$ and the variance is 0.0674 m/s^2 . Likewise, the distribution for the y direction is a mean of $-9 \times 10^{-6} \text{ m/s}^2$ and a variance of 0.0663 m/s^2 .

For this experiment, the displacement in the x and y directions was chosen to be the unit of measurement as seen in Fig. 1. The displacement for the IPS was calculated using the difference of the previous value based on the period of 1.5 s given by

$$\Delta x_{IPS} = x_k - x_{k-1} \quad (1)$$

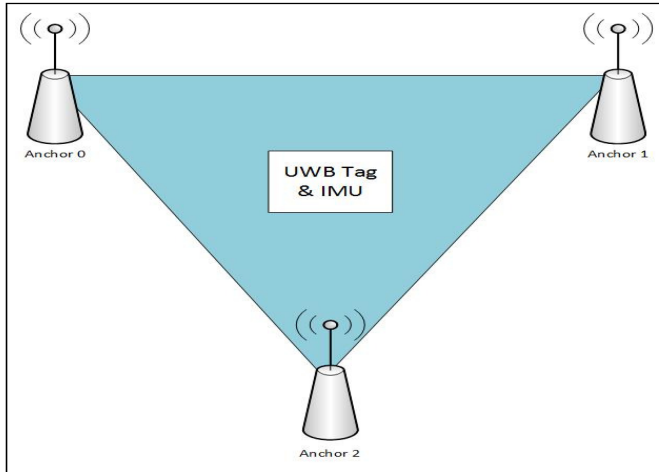


Fig. 2. The setup of the IMU and IPS.

$$\Delta y_{IPS} = y_k - y_{k-1} \quad (2)$$

As given by (3) and (4), the displacement for the IMU can be calculated by integrating the acceleration values considering an initial velocity of 0 meters per second (m/s) since it starts from stationary. The displacement values from IMU given by

$$\Delta x_{IMU} = \left(\frac{1}{2} a_{x_k} t^2 + v_{x_{o_k}} \right) - \left(\frac{1}{2} a_{x_{k-1}} t^2 + v_{x_{o_{k-1}}} \right) \quad (3)$$

$$\Delta y_{IMU} = \left(\frac{1}{2} a_{y_k} t^2 + v_{y_{o_k}} \right) - \left(\frac{1}{2} a_{y_{k-1}} t^2 + v_{y_{o_{k-1}}} \right) \quad (4)$$

where a_{x_k} and a_{y_k} are the acceleration values in the x and y directions, $v_{x_{o_k}}$ and $v_{y_{o_k}}$ are the velocity values in the x and y components, and t is time.

Since the data rate for the IMU is 20 Hz, the mean of the values over 1.5 s was used to match the data rate of the IPS. In addition, this also reduces the variance received from the IMU values to 0.0027 m/s^2 from its original 0.0673 m/s^2 for the x direction, and 0.0047 m/s^2 from its original 0.0663 m/s^2 for the y direction when reading from the IMU at 20 Hz as seen in Fig. 4.

Then, the calculated displacements are input into the Kalman filter and the fused displacement is calculated by,

$$\Delta x_{Fused} = \frac{\Delta x_{IMU} \sigma_{IPS}^2 + \Delta x_{IPS} \sigma_{IMU}^2}{\sigma_{IMU}^2 + \sigma_{IPS}^2} \quad (5)$$

$$\Delta y_{Fused} = \frac{\Delta y_{IMU} \sigma_{IPS}^2 + \Delta y_{IPS} \sigma_{IMU}^2}{\sigma_{IMU}^2 + \sigma_{IPS}^2} \quad (6)$$

Afterwards, the fused displacement is added to the last known position to produce a precise location estimate. This recursive feature of the Kalman filter allows it to be used in real-time applications, requiring only the latest state and the current state for its calculations.

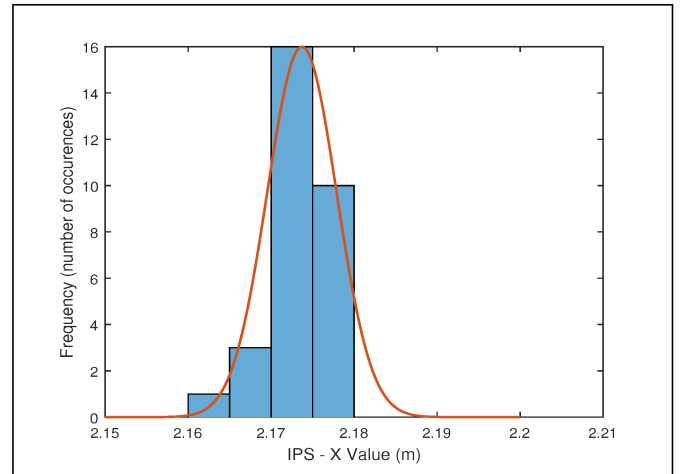


Fig. 3. Histogram and a scaled Gaussian function representation of the raw IPS values.

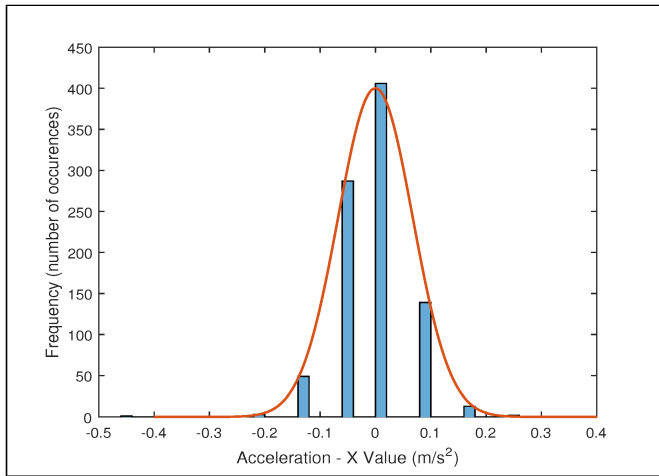


Fig. 4. Histogram and a scaled Gaussian function representation of the raw IMU values.

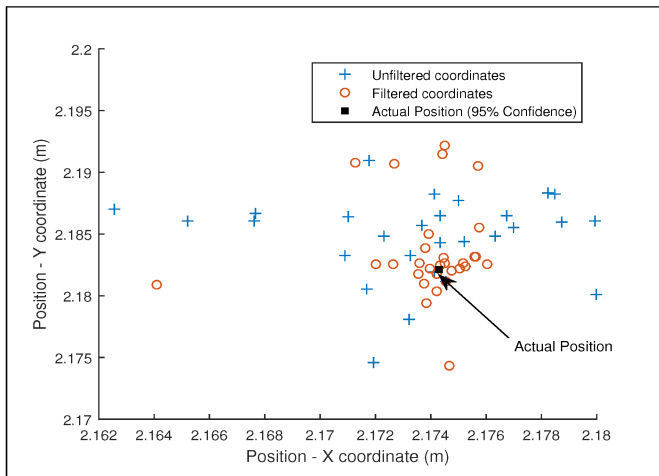


Fig. 5. Comparison of filtered vs unfiltered IPS coordinates.

IV. RESULTS

Accordingly, values from the IPS and IMU were used and filtered in real time to achieve a more accurate position. Fig. 5 shows the comparison of the coordinates position using the IPS, the coordinates position using both the IPS and IMU after the Kalman filter, and the actual position with 95% confidence. The unfiltered coordinates at the end of the experiment is (2.1800 m, 2.1860 m) resulting in a drift of 0.0069 m. In contrast, the filtered coordinates is (2.1760 m, 2.1825 m) resulting in a drift of only 0.0017 m. Furthermore, it can be clearly seen that the unfiltered coordinates have a much greater spread compared to the filtered coordinates. The corresponding variance for the filtered coordinates is 0.0022 m compared to its original 0.0044 m for the x component and the filtered variance is 0.0039 m compared to its original 0.0042 m for the y component.

V. CONCLUSION

In this paper, the aim is to present an indoor positioning system for autonomous robots applications by using sensor

fusion. The system is based on the integration of an UWB positioning system and an IMU. The proposed system has been introduced by describing its architecture and presenting some experimental results for each system. Accordingly, the accumulated data were evaluated using an EKF. The experimental results have shown that a significant increase of accuracy can be reached by using sensor fusion. Although further tests with movement of the autonomous robot are needed to fully verify the system, the error for this system was reduced by 75% of its original error. Integrating INS and UWB positioning provides a higher dynamic range and improved performance than possible with any of the individual systems. Fusion of different sensor systems and evaluation using Kalman filtering enables therefore real-time capability. The experiment is done with LOS between UWB anchors and tags. For future work we can look for the different concepts to mitigate increased signal outages due to higher NLOS and multipath conditions as conducted in [13], [14]. Moreover, the implementation of a Kalman filter with SLAM algorithms should further improve the accuracy for indoor positioning, especially for autonomous robots in mobile scenarios. Finally, a localization technique that delivers accurate position estimates within a few centimeters should allow for future applications of autonomous robots in parking garages, underground areas, and large warehouses.

REFERENCES

- [1] Q. L. Yuan Xu, Xiyuan Chen, "Autonomous integrated navigation for indoor robots utilizing on-line iterated extended Rauch-Tung-Striebel smoothing," *Sensors* 2013, no. 13, pp. 15 937–15 953, 2013.
- [2] V. Renaudin, B. Merminod, and M. Kasser, "Optimal data fusion for pedestrian navigation based on uwb and mems," in *Position, Location and Navigation Symposium, 2008 IEEE/ION*. IEEE, 2008, pp. 341–349.
- [3] W. c. Park and M. h. Yoon, "The implementation of indoor location system to control zigbee home network," in *2006 SICE-ICASE International Joint Conference*, Oct 2006, pp. 2158–2161.
- [4] F. Evennou, FrdricMarx, "Advanced integration of wifi and inertial navigation systems for indoor mobile positioning," *EURASIP Journal on Advances in Signal Processing*, vol. 2006, pp. 1–12, 2006.
- [5] R. Faragher, "Understanding the basis of the kalman filter via a simple and intuitive derivation [lecture notes]," *IEEE Signal Processing Magazine*, vol. 29, no. 5, pp. 128–132, 2012.
- [6] G. P. Hancke and B. Allen, "Ultrawideband as an industrial wireless solution," *IEEE Pervasive Computing*, vol. 5, no. 4, pp. 78–85, 2006.
- [7] "Ubisense," Accessed February 22, 2017. [Online]. Available: <http://ubisense.net>
- [8] "Zebra makes businesses as smart and connected as the world we live in," Accessed February 22, 2017. [Online]. Available: <https://www.zebra.com/us/en.html>
- [9] "Indoor positioning systems (ips) - rtl solutions — decawave," Accessed February 22, 2017. [Online]. Available: <http://www.decawave.com>
- [10] "Home - stmicroelectronics," Accessed February 24, 2017. [Online]. Available: <http://www.st.com>
- [11] J. Carlson, "Mapping large, urban environments with gps-aided slam," Ph.D. dissertation, Carnegie Mellon University.
- [12] J. Jun, R. Guensler, and J. Ogle, "Smoothing methods to minimize impact of global positioning system random error on travel distance, speed, and acceleration profile estimates," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1972, pp. 141–150, 2006.
- [13] B. S. K. E. J. P. Paul Yoon, Shaghayegh Zihajehzadeh, "Robust biomechanical model-based 3-d indoor localization and tracking method using uwb and imu," *IEEE Sensors Journal*, vol. 17, no. 4, pp. 1084–1096, 2016.
- [14] M. Yavari, "Indoor real-time positioning using ultra-wideband technology," Master's thesis, University of New Brunswick.