System Design for Quadrant-Based Indoor Localization of Emergency Responders

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***Abstract*—This work is aimed at realizing a prototype of a personalized wearable technology to localize emergency responders in GPS-denied indoor environments. In this paper, we specifically focus on the design of a 2D quadrant-based localization system using low-cost inertial sensors and ultra-wideband (UWB) based positioning system. A Kalman filter is implemented to reduce the error produced by the gyroscope and a velocity-reset method is introduced to mitigate the random walk errors in velocity estimate from the accelerometer data. The system is tested in a 2D environment and the results demonstrate that a quadrant-based localization accuracy can be achieved when compared to the ground truth.**

***Index Terms*—Indoor localization, Ultra-wideband positioning, velocity-reset, Wearable technology, Kalman Filter**

I. Introduction

Research on indoor localization technologies has picked up pace in the last few years. When it comes to localization and navigation in outdoor environment, we have standard systems in place, like Global Positioning System (GPS), which works very well in positioning and localizing. However, results show that GPS, when used in indoor environment, doesn't produce results at the same level of efficiency. The reason for this is the presence of obstacles that can weaken the signal of GPS in indoor environment (e.g. walls, buildings). Also, in indoor environment, there is a very high potential for existence of materials that can add very high noise to the GPS signal. As pointed out by Mautz, "ability to locate objects and people indoors remains a substantial challenge, forming the major bottleneck preventing seamless positioning in all environments [1]." This warrants a need for research in GPS-less localization methods to establish a standard set of algorithms for Indoor localization.

For any type of localization, the robustness of the algorithm mainly depends on some key factors - Accuracy, Cost, Usability, Complexity of the technology used, Performance and Privacy. Over the years several technologies were used to identify the current position of the user while navigating indoors that include Magnetic and Optical Vision, Infrared (IR), Audible sound, Radio Frequency, Pedestrian Dead Reckoning and Ultrasound/Ultrasonic. Its not yet clear which, if any, technology will become dominant. Indoor localization is more application specific and the use of technology varies based on the importance given to the key factors and also the environment where localization needs to be achieved. [2] introduces a pre-processing technique that can improve the accuracy of Indoor localization in health-care applications using Bluetooth Low Energy (BLE).

[3] talks about an Infrared Protocol (IRP) for Indoor positioning using Light Emitting Didoes (LEDs) with an aim to reduce the positioning time without compromising on the accuracy. [4] explored the idea of fusing Magnetic and Visual sensors to achieve infrastructure free indoor localization with emphasis on precision. There are also several infrastructure-based indoor localization systems, [5] which is RF-based and introduces algorithms based on WiFi Technology.

High accuracy is possible to achieve at a cost of greater computational complexity, which leads to higher costs. [6] talks about Fingerprint based localization which uses deep learning techniques and effectively reduces the localization errors. [7] introduces localization using a special kind of radar sensor which radiates continuous transmission power and also change its operating frequency during the measurement (FMCW), which is basically a Radio-frequency based approach and infrastructure-free.

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Taking a close look at each one of these technologies and the approach followed, validates the fact that Indoor localization is highly application specific. And hence, the effectiveness of a system will be highly dependent on requirements in and flexibility of factors like accuracy, cost. Our interviews with over 100 firefighters, chiefs, manufacturers of firefighting equipment and regulators from helped us come to a clear conclusion regarding the accuracy requirements in our system that can aid for a beneficial and cost-effective localization of Emergency responders. As mentioned in [8], localizing an emergency responder to a floor and quadrant of building is accurate enough for the Commanding officer to take decisions swiftly when there is a sudden change in the environment.

Our goal in a nutshell is to develop a wearable technology to streamline the process of Personnel Accountability Report (PAR) checks conducted by the incident commander and to localize the firefighter/first-responder to a floor and quadrant of the building. Our motivation for the approach towards the problem is clearly outlined in [8]. In this paper, we are presenting our progress in building such a system, using 2- Inertial Measurement Units (IMUs), placed $180°$ out of phase with each other in our system and an Ultra Wide Band system that can be used as an asynchronous external position update to negate the drift errors in the localization estimation caused by the increasing inaccuracies in the acceleration estimation by IMUs over time which are used to localize to a quadrant in a floor. The remainder of the paper is structured as follows. Section II explains the algorithms used to reduce the error in yaw data obtained from the IMUs and the methodology to integrate UWB information with IMU data as a part of the position update step. Section III talks about the experiments and analysis of the results obtained. Section IV talks about Conclusion and Future work.

II. Methodology and Algorithm

Typically an IMU is an assortment of inertial sensors including a 3-axis Accelerometer, a 3-axis Gyroscope and a 3-axis Magnetometer. These provide acceleration data, angular velocities and orientation relative to earth magnetic field of the device respectively. And it's common knowledge that these inertial sensors are subjected to several common sources of errors, like bias, scale factor, misalignment, temperature dependencies, and gyro g-sensitivity. Errors like bias and scale factor are easy to deal with. Most of these error sources can be dealt or minimized with a good calibration process. Our primary goal is to achieve and accurate orientation estimate by fusing Heading measurement from Magnetometer and Angular rates from Gyroscope using a Kalman filter.

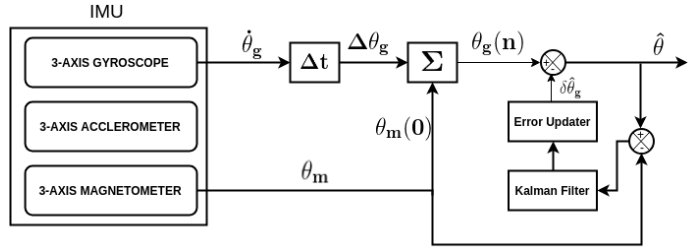

Fig. 1. Gyroscope Error Model

A Magnetometer (compass) provides long-term stability to output data where as gyroscope measures faster changes in orientation (short-term accuracy) and hence compensate for the weakness of compass in this aspect. In Layman's terms, fusion helps to maximize the strengths of individual sensors. For our initial testing, we selected an IMU which has a quaternion based, drift compensated Kalman filter implemented, as it is understood that a quaternion based solution ensures reliable operation without the traditional problems associated with gimbal-lock. Based on the results, the idea is to implement an improved version of [9] for the final product.

The IMU data we are concerned about is accelerometer data and orientation quaternion. As our goal is to achieve a quadrant-level accuracy in 2D localization, this quaternion data is converted to Roll-Pitch-Yaw (RPY) and yaw (θ) is estimated by fusing Magnetometer and Gyroscope data, an added layer of Kalman filter. Yaw from the digital compass contribute to determine an absolute angle and to minimize drift produced by the gyroscope. As we know that yaw from gyroscope is estimated by integrating the angular data w_z and its error accumulates over time, which leads to a short term accuracy and long term drift. Also, magnetic sensing characteristics can lead to distortion in the estimated angle.

$$\theta(t) = \theta_0 + \int w_z(t)dt \tag{1}$$

$$\Delta\theta_g(t) = \dot{\theta}_g(t)\Delta t \tag{2}$$

We get discrete angular rates from gyroscope. This data is numerically integrated to obtain increments $\Delta\theta_g$.

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And for the initial yaw estimate of gyroscope, we use the initial value of the magnetometer. That means

$$\theta_g(0) = \theta_m(0) \tag{3}$$

Errors of yaw angles obtained from yaw rate of gyroscope are estimated and and is fed to our error updater of our Kalman filter. The error updater accumulates them and in turn calculates the total estimated yaw error, $\delta\hat{\theta}_g$. This is subtracted from gyroscope yaw angle, θ_g and provides an estimate of yaw angle $\hat{\theta}$.

$$\hat{\theta} = \theta_g - \delta\hat{\theta}_g \tag{4}$$

And the input to the Kalman filter is the difference corrected gyroscope yaw, $\hat{\theta}$ and yaw angle from magnetometer, θ_m. This implementation of Kalman filter is based on [10], which itself is based on previous studies in the field [11], [12]. Figure 1. shows the modelling of gyro error. Talking about the Kalman filter part, gyroscope errors such as scale factor error, bias and Gaussian noise is modelled by taking each of these errors as functions of forcing functions, which results in a linear continuous dynamic model of the form

$$\dot{\mathrm{x}} = \boldsymbol{F}x + u \tag{5}$$

where x is a vector of gyro errors, $\boldsymbol{F}$ is a fundamental matrix and u is a vector of continuous random process disturbances. This continuous model is discretized to obtain the state transition model, which gives the transition matrix (Φ_k) and white noise estimate (w_k) using inverse-laplacian transform. The process noise co-variance (Q_k)is obtained using the transfer function method introduced in [12]. Error co-variance matrix is obtained from the variance of compass measurement errors and this is computed by taking some sample data offline. Kalman filter has 2 steps: Prediction, Update. In our system, the switch from update-mode to prediction-mode is done when the acceleration differs from 1g by more than a threshold. And the algorithm switches to prediction node, when the change in yaw from gyro and compass ($\Delta\theta_{comp} - \Delta\theta_{gyro}$) is insignificant. Significant difference implies there is Magnetic disturbance in effect, which could be the case for our application, where the environment is volatile and unknown. The pseudo code for the Kalman filter loop is given in Algorithm 1.

Algorithm 1 Kalman Filter Loop

1. Initialize vector of gyro error estimates, Co-variance matrix of filtration errors and Error update output of Kalman filter

$$\hat{x}_{0/0} = 0, P_{0/0} = I, \delta\hat{x}_0 = 0$$

for iteration k in loop: 2. Prediction of state estimate before measurement update and Co-variance matrix of predicted errors (Time update).

$$\hat{x}_{k+1/k} = \Phi_k\hat{x}_{k/k} - \delta\hat{x}_k$$

$$P_{k+1/k} = \Phi_k P_{k/k}{\Phi_k}^T + Q_k$$

3. Calculation of Kalman gain and measurement vector for current step (Update correct)

$$K_{k+1/k} = P_{k+1/k}{H_k}^T(H_k P_{k+1/k}{H_k}^T + R_k)^{-1}$$

$$z_{k+1} = x_{k+1/k}(0) + v_c$$

4. Estimate the predicted state after measurement update and Co-variance matrix of filtered state vector

$$\hat{x}_{k+1/k+1} = \hat{x}_{k+1/k} + K_{k+1}(z_{k+1} - H_k\hat{x}_{k+1/k})$$

$$P_{k+1/k+1} = (1 - K_{k+1}H_k)P_{k+1/k}(1 - K_{k+1}{H_k}^T) + K_{k+1}R_k{K_{k+1}}^T$$

5. Estimate the error correction (Kalman filter output)

$$\delta\hat{x}_{k+1} = \delta\hat{x}_k + \hat{x}_{k+1/k+1}$$

6. Increment $k : (k = k + 1)$ and go back to Step 2

Algorithm 2 Velocity reset

1. Set buffer size using window size and sampling frequency.

$$bufferSize = (mov\_win\_mul/delta\_t)$$

2. If buffer is full, compare RMS error of a_z and RMS_Threshold.
3. Reset velocities

$$v_x =,\ v_y = 0\ if\ a_z < RMS\_Threshold$$

Bias and drift in the accelerometer readings results in Random-walk errors in calculated velocity. These can be mitigated using Velocity-reset technique. Accelerations in x,y,z directions are recorded over a window, which are used to calculate the magnitude of net acceleration. This is compared with a threshold and the current velocity is

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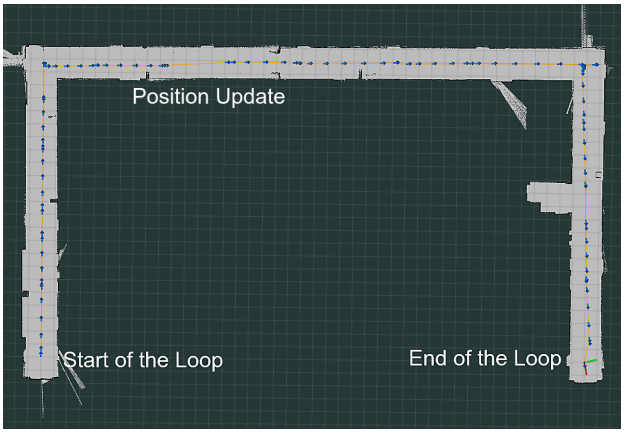

Fig. 2. Trajectory of the System

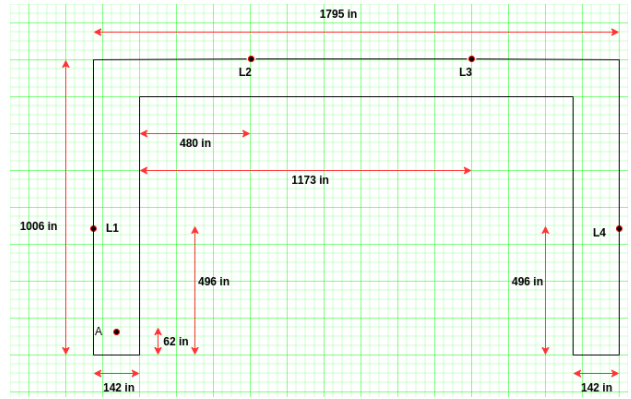

Fig. 3. Map Layout with Dimensions and Locations of Tags (L1, L2, L3, L4)

reset to 0 if this value is less than the threshold. These are tuned to obtain optimal threshold and window size which are used in all our subsequent experiments. The pseudo code is detailed in Algorithm 2.

III. Experiments and Results

For our experiments, we used two miniature, high performance IMUs, VN-100, developed by VectorNav Technologies. For position update using UWB technology, we used the development kit of Pozyx Labs, which contains 4 anchors and 1 tag. These anchors are dropped in 4 positions of the testing environment as shown in Figure 3. For ground truth comparison, anchor position data is measured with respect to the world frame (map) and fed to the algorithm.

The tag is placed right next to the IMUs and the distance between the tag and both IMUs is too small to effect our desired accuracy and hence ignored.

The idea behind using 2 IMUs is to track the backward motion of the individual based on the acceleration profiles over a small window and detect the direction of the motion. This is because a single IMU data is not enough to check direction of acceleration, because going backwards and braking while moving forward would show results in the same direction.

Currently, our tracking system includes 2 IMUs and a tag. This is moved around using a small cart. Ground truth information, such as the map of the environment, initial position of the system with respect to the map, are visualized in rViz along with the estimated position of the system calculated using the IMU data. External position update, which is the location of tag, is fed as an asynchronous input upon request.

Figure 2 shows the rViz visualization of the trajectory of the system. For this experiment, we started at the left end of the map, which is the corridor of a floor, and completed one loop moving along the corridor. A position update is received from the tag of the UWB system, which is used to adjust the position. For this experiment, position information is requested only once, at half way point in the trajectory, and the difference in the current position estimates using IMU and UWB is only 2 inches. The location where an update is requested is clearly marked in Figure 2.

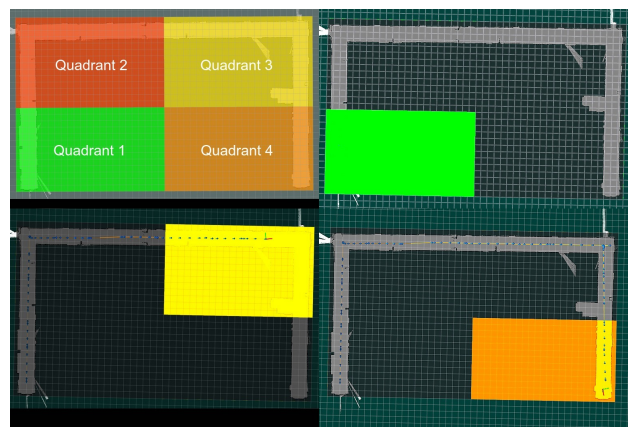

Fig. 4. Top Left: Map divided into Quadrants with each color coded; Top Right: Localizing in 1st Quadrant; Bottom Left: Localizing in 3rd Quadrant; Bottom Right: Localizing in 4th Quadrant

But, as established, our goal is to localize within a quadrant and so, we divided our map into 4 quadrants, color-coding each as shown in Top left image of Figure 4. So, for our next experiment, we collected data over several loops and visualized the quadrant tracking. Over 10 loops, which took nearly 24 minutes to complete, quadrant information obtained with a position update once every loop and when compared with the ground truth based on the time stamp information, localization to

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a quadrant of the map is estimated with a 100% accuracy. Position update from the UWB tag is fed to the system 5 times over the period, once every 2 loops. Figure 4. also shows 3 frames from the visualization output of the trajectory of the person. Figure 5 shows the trajectory in both X and Y directions as a function of time. We can clearly see the loop which starts and ends at X = 0.

As you can see the quadrant information is identified based on the current position estimate and as the length of each quadrant is very large, the probability for a wrong estimation of quadrant, in theory should very low, and our result backs the theory.

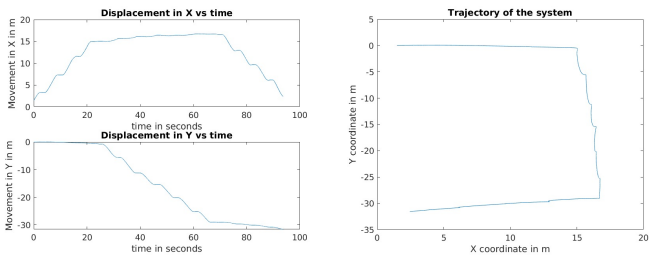

Fig. 5. Left: Displacement of X and Y w.r.t Time; Right: Trajectory of the System plotted as a Signal

IV. Conclusion and Future Work

System level design to achieve indoor localization to a quadrant on a particular floor is explained. Advantages and reasoning behind localization with respect to quadrants is clearly established. Algorithm used for estimation of yaw error, which is used to correct the yaw value used for 2D position estimate is presented in detail. We believe our approach is a promising first step towards delivering a proof-of-concept wearable system for indoor localization of emergency responders. We are working towards building an infrastructure-free system by making the UWB and IMU sensors co-dependant, which means that we don't need to know the map of the building or need to pre-deploy the anchors. The only required parameter would be the initial position of the fire-fighter when the wearable system starts tracking.

Our vision is for the firefighter to drop these anchors, like bread crumbs while moving around inside a building on a particular floor and the anchors position is recorded, with respect to the initial position based on the position data from IMU, whose position estimate will not effect our accuracy requirements till the deployment is complete. Future work will be focused on achieving this. As the goal is for the system to localize to a floor and quadrant, we will continue working towards a solution to accurately predict the height information using barometric sensors.

It is understood that the environment firefighter enters is highly volatile and unpredictable. Position situational awareness remains a problem in incident and emergency response, but the evolving nature of environments is the biggest issue. One of the main future goals is the demonstration of this application in varied environments. Especially the impact on the overall accuracy of the localization system when the responder move in and out of the building. Also, the ability of the sensors to function the same way they do in regular environments and room temperatures is unknown. So, we identified that a set of controlled experiments to evaluate the performance of the sensors by simulating the conditions like high temperatures, varying magnetic fields, due to the effect of fire on the number of ionized particles in the environment are warranted.

References

[1] Rainer Mautz and Sebastian Tilch, "Survey of optical indoor positioning systems," in *Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on*. IEEE, 2011, pp. 1–7.

[2] Shanatip Choosaksakunwiboon, Chawin Terawong, Suppakorn Suttisirikul, Isara Anantavrasilp, Surapa Thiemjarus, Sodsai Wisadsud, and Kamol Kaemarungsi, "A pre-processing technique for ble-based indoor localization," in *Proceedings of the 12th International Convention on Rehabilitation Engineering and Assistive Technology*. Singapore Therapeutic, Assistive & Rehabilitative Technologies (START) Centre, 2018, pp. 241–244.

[3] Olaoluwa R Popoola, Wasiu O Popoola, Roberto Ramirez-Iniguez, and Sinan Sinanović, "Design of improved ir protocol for led indoor positioning system," in *Wireless Communications and Mobile Computing Conference (IWCMC), 2017 13th International*. IEEE, 2017, pp. 882–887.

[4] Zhenguang Liu, Luming Zhang, Qi Liu, Yifang Yin, Li Cheng, and Roger Zimmermann, "Fusion of magnetic and visual sensors for indoor localization: Infrastructure-free and more effective," *IEEE Transactions on Multimedia*, vol. 19, no. 4, pp. 874–888, 2017.

[5] Llewellyn Liu Wee Ling, "Indoor rf positioning system using collaborative trilateration method," 2017.

[6] Xuyu Wang, Lingjun Gao, Shiwen Mao, and Santosh Pandey, "Csi-based fingerprinting for indoor localization: A deep learning approach," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 1, pp. 763–776, 2017.

[7] Tianjun Huang, Jiutao Hao, Zhizhang David Chen, Guangjun Wen, Jinyan Li, and Huapeng Zhao, "An indoor fmcw localization system with the application of the extended kalman filter," in *2018 IEEE MTT-S International Wireless Symposium (IWS)*. IEEE, 2018, pp. 1–4.

[8] Velin Dimitrov, Jose Vazquez, and Taşkın Padır, "Locater: Localization and accountability technologies for emergency responders," in *Technologies for Homeland Security (HST), 2017 IEEE International Symposium on*. IEEE, 2017, pp. 1–4.

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[9] Kaiqiang Feng, Jie Li, Xiaoming Zhang, Chong Shen, Yu Bi, Tao Zheng, and Jun Liu, "A new quaternion-based kalman filter for real-time attitude estimation using the two-step geometrically-intuitive correction algorithm," *Sensors*, vol. 17, no. 9, pp. 2146, 2017.

[10] Pedro Neto, Nuno Mendes, and A Paulo Moreira, "Kalman filter-based yaw angle estimation by fusing inertial and magnetic sensing: A case study using low cost sensors," *Sensor Review*, vol. 35, no. 3, pp. 244–250, 2015.

[11] Robert Grover Brown, Patrick YC Hwang, et al., *Introduction to random signals and applied Kalman filtering*, vol. 3, Wiley New York, 1992.

[12] P Kaniewski and J Kazubek, "Integrated system for heading determination," *Acta Physica Polonica-Series A General Physics*, vol. 116, no. 3, pp. 325, 2009.

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