A Combined PDR and Wi-Fi Trilateration Algorithm for Indoor Localization

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Abstract—**Indoor localization using Wi-Fi or pedestrian dead reckoning (PDR) has several limitations in terms of Wi-Fi signal fluctuations and PDR drift errors. To overcome these limitations, we propose a sensor fusion framework for Wi-Fi and PDR systems. The proposed sensor fusion will overcome the PDR drift errors by analysing the Wi-Fi signal strength and the PDR results will compensate the Wi-Fi signal fluctuations. Based on the experiments conducted, results show that the proposed fusion indoor positioning algorithm shows high position accuracy over Wi-Fi localization and PDR systems when used independently. Our proposed combined position estimation algorithm achieves an improved average localization accuracy of 1.6 m when compared to the Wi-Fi and PDR systems when used independently.**

Index Terms—**Indoor localization, Wi-Fi, smart phone, quaternion, Kalman filter, sensor fusion, Pedestrian dead reckoning (PDR), Android-based smartphone, Trilateration, RSSI**

I. Introduction

Position estimation using pedestrian dead reckoning (PDR) [1] is more convenient compared to that using Wi-Fi indoor positioning [2]. However, smartphone sensor data contain drift errors which accumulate as the experimentation time increases hence degrading localization performance. In order to compensate the drift errors from the PDR system based on smartphone sensor data, Wi-Fi based positioning using receiving signal strength indicator (RSSI) signals is an alternative approach. Again, the performance of Wi-Fi indoor positioning system depends on the Wi-Fi RSSI signal fluctuations and line of sight conditions. Non-line of sight conditions from the Wi-Fi access points and the receiver as well degrade the localization performance. To achieve high position accuracy, this paper proposes a combined algorithm that uses both smartphone-based PDR and Wi-Fi indoor positioning. The PDR systems utilize the accelerometer, magnetometer and gyroscope for localization [3]. The Wi-Fi system uses RSSI signals as data for localization [4]. The proposed position estimation system takes advantage of both positioning systems, hence achieving a significant improvement in the position accuracy. The basic idea of combining the two systems is that the PDR systems will use the RSSI signal for compensating sensor errors and the Wi-Fi systems will use the PDR results for the large RSSI fluctuation problem. The combined system achieves a better performance compared to when the individual systems are used independently.

II. RELATED WORK

The basic idea of the PDR positioning is explained by Shin *et al.* [5]. In their work, a status recognition algorithm for step length estimation was used. The status recognition algorithm was used to reduce the accelerometer sensor errors. Our proposed system uses the Kim's approach [6] for the step length estimation instead of the status recognition algorithm. The status recognition algorithm increases the system complexity as compared to Kim's approach. Kakiuchi *et al.* [7] introduced a novel model of the stride length estimation for pedestrian motion. The proposed system is capable of switching the estimation method according to whether the pedestrian is walking or running. This mode switching makes the stride length estimation more adaptive and it improves the PDR system performance. Tian *et al.* [8] have reported a multi-mode PDR System. In their proposed system, they detected the pedestrian motion based on the modes of carrying the smartphone. The experiment results show that the proposed system has an average position accuracy of 98.91% in real-time. Ilkoviˇcová *et al.* [9] proposed an adaptive step length method to the PDR system for smartphone sensor errors. The proposed method significantly increases the accuracy of the PDR system and reduced the accumulated errors.

The basic Wi-Fi trilateration concepts are described by Mahiddin*et al.* [10]. They implemented a trilateration technique to determine the position of users in indoor areas based on Wi-Fi signal strengths from access points (AP) within the indoor vicinity. The problems associated with the Wi-Fi trilateration algorithm are explained by Cook *et al.* [11]. They introduced some proposals to improve the precision of the trilateration algorithm. An improved indoor positioning algorithm based on RSSI-trilateration technique for internet of things (IOT) has been studied by Rusli *et al.* [12]. They have proposed a model which includes the implementation of trilateration technique to determine the user position.

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The first work considering the integration of Wi-Fi and PDR for the indoor localization is reported by Evennou *et al.* [13]. They proposed a Kalman filter and a particle filter for sensor fusion. Another sensor fusion work is explained by Wang *et al.* [14] using particle filters. Leppäkoski *et al.* [15] used an extended Kalman filter for integrating the Wi-Fi and PDR systems. Carrera *et al.* [16] presented a real-time indoor localization approach that fuses Wi-Fi RSSI readings, inertial measurement units (IMUs) and the floor plan information in an enhanced particle filter. The proposed method achieved the average tracking error of 1.7 meters with 90% position accuracy.

In the above literature review, we discussed different types of indoor localization systems and fusion techniques. The sensor fusion techniques discussed require further improvement related to the positional accuracy. The proposed system combines the results from the Wi-Fi and PDR systems by using Kalman filter. In Wi-Fi localization, we use the trilateration algorithm for position estimation. In the trilateration algorithm, we use free space path loss (FSPL) model [17] for distance estimation. The estimated distance depends on the Wi-Fi RSSI signal strength. The estimated distance is used for the position estimation algorithm. In the PDR system approach, we use two sensor fusion techniques for reducing the smartphone sensor errors. We use a sensor fusion technique for pitch and roll estimation and another sensor fusion technique for heading estimation. The pitch and roll values are estimated from the accelerometer and gyroscope sensor-fusion. The heading is estimated from the gyroscope and magnetometer sensor fusion. The proposed system uses all smartphone sensors for the position estimation. The position in the PDR system is estimated from the step length and heading information.

III. PROPOSED POSITION ESTIMATION ALGORITHM FOR INDOOR LOCALIZATION

The proposed system is the combination of the PDR and Wi-Fi systems. The PDR system utilizes the accelerometer, magnetometer and gyroscope sensors for the position estimation. Whereas, the Wi-Fi positioning system uses the Wi-Fi RSSI signal for the position estimation. Fig. 1 shows the proposed system for the indoor localization using the PDR and Wi-Fi positioning.

The first block of the proposed system is the PDR position estimation algorithm. The PDR system uses the accelerometer, gyroscope and magnetometer for the position estimation. Three algorithms are used for localization in the PDR system. The first algorithm used in the PDR system is the step length algorithm. The step length algorithm uses the peak of accelerometer data for detecting the pedestrian step. The second algorithm used in the PDR system is the heading estimation. The heading estimation uses the magnetometer and gyroscope data for estimating the heading of the pedestrian. The last algorithm used in the PDR system is the position

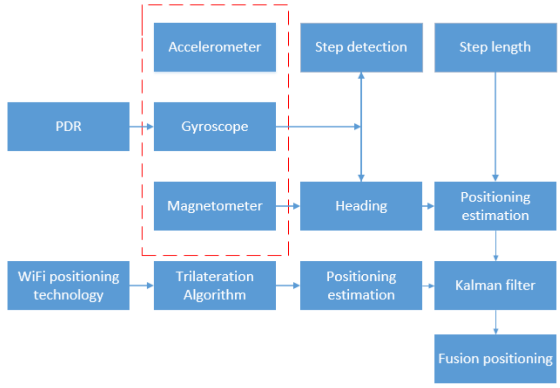

Fig. 1: Indoor localization based on the PDR and Wi-Fi trilateration Algorithm.

estimation. The position estimation algorithm uses the step length data and heading information for detecting pedestrian position. The second block of the proposed system is the Wi-Fi positioning. In Wi-Fi positioning approach, we use the Wi-Fi RSSI signals for the position estimation. The smartphone Wi-Fi module receives Wi-Fi signals and based on the signal strength we estimate the distance between the smartphone and Wi-Fi access points. For distance estimation we used the FSPL model. The estimated distance information is used for the position estimation. The last stage of the proposed system is the sensor fusion. A Kalman filter [18] with a suitable system model achieves the sensor fusion for the proposed system.

A. PDR Positioning

In the PDR approach, we use three smartphone sensors for position estimation. For collecting data from smartphone sensors, we used the sensor stream inertial measurement unit and global positioning system android application. The android application gives accelerometer, gyroscope and magnetometer values and these values were stored in the smartphone. The PDR system used in the proposed system consists of four stages. The step length estimation of the pedestrian is the first stage. The step length is estimated from filtered accelerometer data. For step length estimation, the peaks of the accelerometer data are used for step detection. The detected steps are then used for step length estimation. Where, the step length (SL) is estimated by Kim's approach [19] as

$$\mathrm{SL} = k \times \sqrt[3]{\frac{\sum_{k=1}^{N} |a_k|}{N}} \tag{1}$$

where a_k denotes the average acceleration during a step and k is a constant value and is modified due to different placement of the sensor. The second stage of the PDR algorithm is to estimate the pitch and roll values from the accelerometer and gyroscope sensors. The proposed

PDR approach uses a sensor fusion algorithm for pitch and roll estimation. The three axis data from accelerometer sensor are $a_{acc} = (a_x, a_y, a_z)$ and g denotes gravity acceleration. The pitch and roll angles are given by

$$\text{Pitch angle}(\theta) = \sin^{-1}\left(\frac{a_y}{g}\right) \tag{2}$$

$$\text{Roll angle}(\phi) = \tan^{-1}\left(\frac{a_x}{a_z}\right) \tag{3}$$

The pitch and roll angles from gyroscope sensor are estimated by an integration process. The final pitch and roll angles are estimated by combining the accelerometer and gyroscope values. The Kalman filter [18] is applied for pitch and roll sensor fusion.

Assume X_t is the pitch and roll values of the system and $x = [\,q_0 \quad q_1 \quad q_2 \quad q_3]^T$ is the input where q_0, q_1, q_2, q_3 are gyroscope quaternion values. The state transition of the sensor fusion is expressed as

$$X_t = AX_{t-1} + Gx + v \tag{4}$$

where G is the identity matrix and v denotes the Gaussian noise of the model with zero mean and covariance matrix Q. The noise covariance matrix Q is given by

$$Q = \begin{bmatrix} 0.001 & 0 & 0 & 0 \\ 0 & 0.001 & 0 & 0 \\ 0 & 0 & 0.001 & 0 \\ 0 & 0 & 0 & 0.001 \end{bmatrix} \tag{5}$$

The system model A is defined as

$$A = \frac{1}{2}\begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix} \tag{6}$$

where ω_x, ω_y and ω_z are the three-axis gyroscope data in the device coordinate system. The state variable is defined by the gyroscope quaternion values. Therefore, it is necessary to convert the gyroscope data to quaternion values. The conversion of the gyroscope Euler angles to quaternion values are given by

$$\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} = \begin{bmatrix} \cos\frac{\phi}{2}\cos\frac{\theta}{2}\cos\frac{\psi}{2} + \sin\frac{\phi}{2}\sin\frac{\theta}{2}\sin\frac{\psi}{2} \\ \sin\frac{\phi}{2}\cos\frac{\theta}{2}\cos\frac{\psi}{2} - \cos\frac{\phi}{2}\sin\frac{\theta}{2}\sin\frac{\psi}{2} \\ \cos\frac{\phi}{2}\sin\frac{\theta}{2}\cos\frac{\psi}{2} + \sin\frac{\phi}{2}\cos\frac{\theta}{2}\sin\frac{\psi}{2} \\ \cos\frac{\phi}{2}\cos\frac{\theta}{2}\sin\frac{\psi}{2} - \sin\frac{\phi}{2}\sin\frac{\theta}{2}\sin\frac{\psi}{2} \end{bmatrix} \tag{7}$$

The result of above equation is used as the measurement (O_t) for the kalman filter. The measurement function can be expressed as

$$Q_t = HX_t + p \tag{8}$$

Where p denotes the Gaussian noise of gyroscope heading with zero mean and covariance matrix R. The noise covariance matrix R is express as

$$R = \begin{bmatrix} 0.0001 & 0 & 0 & 0 \\ 0 & 0.0001 & 0 & 0 \\ 0 & 0 & 0.0001 & 0 \\ 0 & 0 & 0 & 0.0001 \end{bmatrix} \tag{9}$$

The matrix H is represent by the following form.

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{10}$$

The Kalman filter [18] is applied to solve this linear problem with assumptions of Gaussian noises. The expression contains two parts:

Predicting:

$$x_t = Ax_{t-1} + Gx \tag{11}$$

$$P_t = AP_{t-1}A^T + Q \tag{12}$$

Updating:

$$K_t = P_tH^T(HP_tH^T + R)^{-1} \tag{13}$$

$$x_t = x_t + K_t(O_t - Hx_t) \tag{14}$$

$$P_t = P_t - K_tHP_t \tag{15}$$

The initial values for the state variable and the error covariance matrix are

$$x_0 = [\,1 \quad 0 \quad 0 \quad 0]^T \tag{16}$$

$$P_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{17}$$

The next stage of PDR algorithm is heading estimation. The proposed PDR system uses the magnetometer and gyroscope values for heading estimation. The relation between magnetic strength in device (h_x, h_y, h_z) and global (H_x, H_y, H_z) coordinate system is expressed as

$$\begin{bmatrix} H_x \\ H_y \\ H_z \end{bmatrix} = \begin{bmatrix} \cos\phi & \sin\phi\sin\theta & -\sin\phi\cos\theta \\ 0 & \cos\theta & \sin\theta \\ \sin\phi & -\sin\theta\cos\phi & \cos\phi\cos\theta \end{bmatrix} \begin{bmatrix} h_x \\ h_y \\ h_z \end{bmatrix} \tag{18}$$

Heading γ is then given by

$$\gamma = \tan^{-1}\left(\frac{H_y}{H_x}\right) \tag{19}$$

The heading from gyroscope is estimated from quaternion update values [20]. Heading (HD) from gyroscope is obtained from the following equation

$$\text{HD} = \arctan\left[\frac{2(q_0q_3 + q_1q_2)}{1 - 2(q_2^2 + q_3^2)}\right] \tag{20}$$

Assume S_t is the heading direction and γ is the input of the system. The state transition function of the heading fusion framework is expressed as

$$S_t = AS_{t-1} + B\gamma + w \tag{21}$$

where A and B are identity matrices and w denotes the Gaussian noise of the system with zero mean and variance ϕ . The observation of the system comes from the gyroscope sensor output, $O_t = \arctan\left[\frac{2(q_0q_3+q_1q_2)}{1-2(q_2^2+q_3^2)}\right]$. The observation function can be expressed as

$$O_t = CS_t + r \tag{22}$$

where $C = \left[\begin{array}{cc} 1 & 0 \end{array}\right]$ and r denotes the Gaussian noise of the magnetometer output with zero mean and variance φ. The Kalman filter [18] is applied to solve this problem and the system contains two parts:

Predicting:

$$S_t = AS_{t-1} + B\gamma \tag{23}$$

$$P_t = AP_{t-1}A^T + \phi \tag{24}$$

Updating:

$$K_t = P_tC^T(CP_tC^T + \varphi)^{-1} \tag{25}$$

$$S_t = S_{t-1} + K_t(O_t - CS_{t-1}) \tag{26}$$

$$P_t = P_t - KCP_t \tag{27}$$

The last stage of PDR algorithm is to estimate the position from step length and heading information [21]. The position is expressed as

$$X_k = X_{k-1} + SL\left[\begin{array}{c} \sin(\theta_k) \\ \cos(\theta_k) \end{array}\right] \tag{28}$$

where X_k is the position at time step t, X_{k-1} is the initial position value and θ_k is the heading direction.

B. Wi-Fi Trilateration Algorithm

In the Wi-Fi trilateration approach, we use four access points for position estimation. The four access points are placed at four corners and the distances between the access points and smartphone are estimated from Wi-Fi RSSI values. Fig.2 shows the positioning-based Wi-Fi trilateration method. The distances between smartphone and access points are estimated by using free-space path loss model as [22]

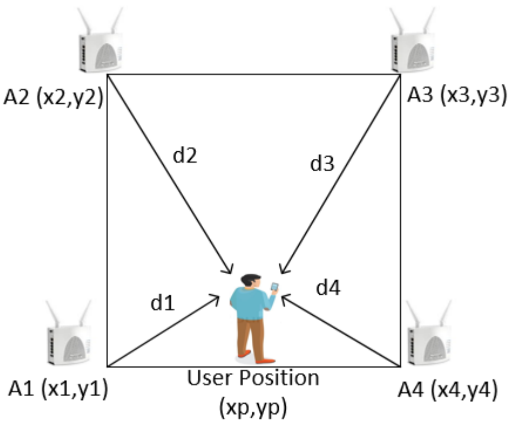

Fig. 2: The positioning-based Wi-Fi trilateration method.

$$\text{FSPL} = 20\log_{10}(d) + 20\log(f) - 22.55 \tag{29}$$

Where, d is the smartphone and access points distance in meters, f is the signal frequency in megahertz, FSPL is received signal strength path loss in dBm.

To calculate the position of smartphone through trilateration method, we used [22] [23] [24]. The distance d_i between smartphone (x_p, y_p) and the access points $A_i(x_i, y_i)$ is expressed through the following relation

$$d_i^2 = (x_i - x_p)^2 + (y_i - y_p)^2 \tag{30}$$

The equation can be expanded as

$$d_i^2 = x_i^2 + x_p^2 - 2x_ix_p + y_i^2 + y_p^2 - 2y_iy_p \tag{31}$$

When we consider a reference point K, then (30) can be rewritten as

$$d_k^2 = x_k^2 + x_p^2 - 2x_kx_p + y_k^2 + y_p^2 - 2y_ky_p \tag{32}$$

Subtracting (31) from (30), then the equation can be expressed as

$$d_i^2 - d_k^2 + x_k^2 + y_k^2 - x_i^2 - y_i^2 = 2(x_k - x_i)x_p + 2(y_k - y_i)y_p \tag{33}$$

Considering $i = 1$ and varying index $k = 2, .., 3$ we obtain (34). The coordinates (x_p, y_p) of the smartphone can be obtained by solving the system of equations described above. We can obtain a linear equations with three unknown, $Ax = b$ where

$$A = \left[\begin{array}{cc} 2(x_2 - x_1) & 2(y_2 - y_1) \\ 2(x_3 - x_1) & 2(y_3 - y_1) \\ 2(x_4 - x_1) & 2(y_4 - y_1) \end{array}\right] \tag{35}$$

$$x = \left[\begin{array}{c} x_p \\ y_p \end{array}\right] \tag{36}$$

$$b = \left[\begin{array}{c} d_1^2 - d_2^2 + x_2^2 + y_2^2 - x_1^2 - y_1^2 \\ d_1^2 - d_3^2 + x_3^2 + y_3^2 - x_1^2 - y_1^2 \\ d_1^2 - d_4^2 + x_4^2 + y_4^2 - x_1^2 - y_1^2 \end{array}\right] \tag{37}$$

The solution of the equations can be (x_p, y_p) that minimizes the δ defined by the following

$$\delta = (Ax - b)^T(Ax - b) \tag{38}$$

$$x = \left[\begin{array}{cc} x_p & y_p \end{array}\right]^T \tag{39}$$

Applying MMSE (Minimum Mean Square Error) method, we can obtain x with the following expression

$$x = (A^TA)^{-1}A^Tb \tag{40}$$

C. Sensor Fusion with Kalman Filter

The different sensor fusion techniques for Wi-Fi and PDR are particle filter [25], hidden Markov model [26], Kalman filter, etc. Our proposed system uses the Kalman filter for Wi-Fi and PDR fusion [27]. The Kalman filter process is computationally light as compared to other sensor fusion techniques.

AssumeX_t is the 2D coordinate of the pedestrian and $d_k = SL\left[\begin{array}{cc} \sin(\theta_k) & \cos(\theta_k) \end{array}\right]^T$ is the input where SL is the step length and θ_k is the heading at time step k. The

$$\begin{bmatrix} 2(x_2-x_1) & 2(y_2-y_1) \\ 2(x3-x_1) & 2(y_3-y_1) \\ 2(x4-x_1) & 2(y_4-y_1) \end{bmatrix} \begin{bmatrix} x_p \\ y_p \end{bmatrix} = \begin{bmatrix} d_1^2-d_2^2+x_2^2+y_2^2-x_1^2-y_1^2 \\ d_1^2-d_3^2+x_3^2+y_3^2-x_1^2-y_1^2 \\ d_1^2-d_4^2+x_4^2+y_4^2-x_1^2-y_1^2 \end{bmatrix} \tag{34}$$

state transition function of the sensor fusion framework is expressed as

$$X_k = AX_{(k-1)} + Gd_k + v \tag{41}$$

where A, G are identity matrices and v denotes the Gaussian noise of the motion model with zero mean and covariance matrix Q. The observation function can be obtained with the Wi-Fi trilateration output, $x = (A^TA)^{-1}A^Tb$. The observation function can be expressed as

$$Z_k = HX_k + p \tag{42}$$

where p denotes the Gaussian noise of the Wi-Fi trilateration output with zero mean and covariance matrix R. Since this sensor fusion is a direct observation problem, we use H as an identity matrix.

Predicting:

$$x_k = Ax_{k-1} + Gd_k \tag{43}$$

$$P_k = AP_{k-1}A^T + Q \tag{44}$$

Updating:

$$K_k = P_kH^T(HP_kH^T + R)^{-1} \tag{45}$$

$$x_k = x_k + K_k(Z_k - Hx_k) \tag{46}$$

$$P_k = P_k - K_kHP_k \tag{47}$$

IV. EXPERIMENTS AND RESULT ANALYSIS

The performance and accuracy of our proposed system are evaluated by a rectangular motion of pedestrian in an indoor environment. The experiment was carried out strictly along the reference path in our college building corridor. Fig.3 shows the experiment skeleton map. The starting point is 10 m far from the corner of the building. The length of the path is 45 m and the width is 37 m. Four access points are considered for the experiment. The four access points are placed at the four corners of the reference path. The pedestrian walked on the reference path.

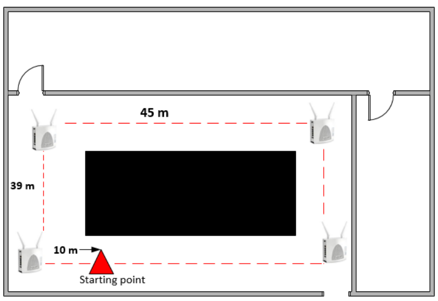

Fig. 3: Skeleton map of the experiment scenario.

Fig. 4 shows the experimental result from the PDR and Wi-Fi systems. The maximum error from the PDR system is 2.9 m and the maximum error from the Wi-Fi system is 2 m.

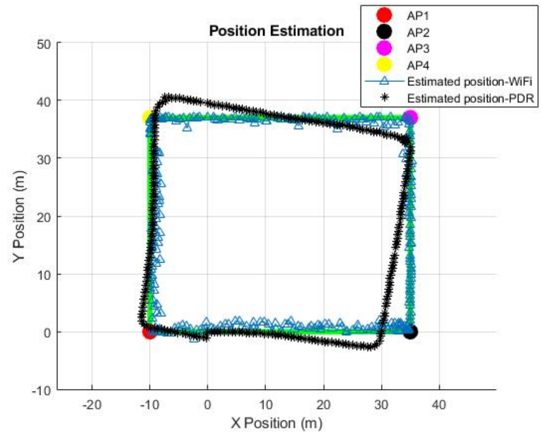

Fig. 4: Position estimation from PDR and Wi-Fi systems.

The experimental results show that indoor localization using PDR and Wi-Fi systems requires further improvement in terms of position accuracy. To improve the position accuracy, we use the proposed sensor fusion system. Fig.5 shows the proposed system results.

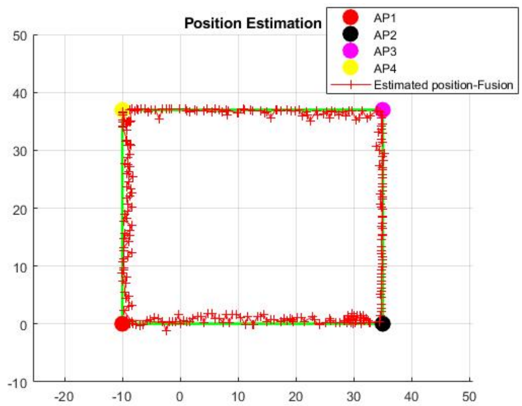

Fig. 5: Position estimation from proposed system.

The maximum position error from the proposed system is 1.6 m. The experimental results show that the proposed system gives highest position accuracy as compared to the individual systems. Table 1 below shows the x and y position errors in the proposed method and individual systems.

Position estimation systems	Maximum Position Error (m)	
	x	y
PDR system	2.9	2.8
Wi-Fi system	1.9	2
Proposed fusion system	1.62	1.6

TABLE I: RMSE of position

V. Conclusion

This paper presented an indoor positioning system using the PDR and Wi-Fi RSSI signals. The proposed position estimation algorithm achieves an improved accuracy compared to when the individual positioning systems are used independently. The maximum position error from the PDR system is 2.9 m and the maximum position error from the Wi-Fi system is 2 m. The proposed system has 1.6 m position error as compared to the ground-truth values. The proposed algorithm utilized the complementary features of the PDR and Wi-Fi system for the indoor positioning. The drift error from the PDR system is compensated by the Wi-Fi RSSI signals. The large Wi-Fi RSSI fluctuations from the Wi-Fi system is overcome by the PDR results. For future work, we intend to add a fingerprint database to the system for the non-line of sight condition problems from the Wi-Fi access points and the receiver module.

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