WiFi/PDR Integrated System for 3D Indoor Localization

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Abstract. In recent years, location-based services LBS have received extensive attention from scholars at home and abroad, and how to obtain location information is a very important issue. The creation of systems for solving problems of positioning and navigation inside buildings is a very perspective, actual and complicated task, especially in a multi-floor environment. To improve the indoor localization performance, we proposed a three-dimensional (3D) indoor localization system integrating WiFi/Pedestrian Dead Reckoning (PDR), where extended Kalman filter (EKF) is used to estimate target location. The algorithm first relies on MEMS in our mobile phones to evaluate the speed and heading angle of the test nodes. Second, for two-dimensional (2D) localization, the speed and heading angle as with as the results of the WiFi Fingerprint-based localization are utilized as the inputs to the EKF. Third, the proposed algorithm works out the height of the test nodes by utilize a barometer and geographical data which have been recorded in real time. Our experimental results in a real multi-layer environment indicate that the proposed WiFi/PDR integrated system algorithm means that the localization accuracy error is at least 1 m lower than WiFi and PDR itself.

Keywords: Wi-Fi fingerprinting · PDR · Extended Kalman Filter
Multi-floor positioning

1 Introduction

Indoor localization technology is widely used in shopping mall navigation, smart home, personnel search and rescue and other fields, with great commercial value and broad application prospects. High-precision indoor localization technology can bring immeasurable value to the enterprise. GPS [1] can provide good positioning accuracy for outdoor localization, but the satellite signal is seriously attenuated indoors [2], which is difficult to meet indoor localization needs and makes indoor localization technology a major challenge. Many indoor localization technologies utilize integrated sensors to assist in indoor localization systems to improve localization accuracy. Among them, Kalman filter is one of the widely used data fusion methods, but due to indoor multipath effect and

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wall attenuation, Kalman filter is difficult to accurately describe indoor signals. Compared with outdoor scenario, indoor localization and navigation methods usually require higher accuracy and better environmental adaptability. In this situation, many localization technologies have been studied and even utilized in many special scenarios, such as WiFi fingerprinting, RFID (Bluetooth RFID) and other technologies [3–5].

It is well known that due to the low cost of equipment, extensive infrastructure deployment and high positioning accuracy, WiFi fingerprint based localization technology is very popular in indoor and underground environments [6–10]. However, complex indoor environments can cause blocking, attenuation, and multipath effects on Received Signal Strength Indication (RSSI) measurements. And RSSI is difficult to reflect accurate location information, which degrades the accuracy of fingerprint-based positioning. In order to solve this problem, some positioning technologies integrating WiFi fingerprint recognition and MEMS sensors are proposed in [11–15].

MEMS sensor based positioning techniques have been widely adopted for most mobile terminals currently integrate different types of sensors, such as accelerometers, magnetometers and barometers. In most cases, MEMS sensor-based positioning has low infrastructure costs and satisfactory positioning [16–19]. However, cumulative errors associated with MEMS sensor based positioning have long been considered one of the most important issues.

The main contributions of this paper are as follows. First, we use gait detection to optimize the speed calculation. In addition, we use the quaternion algorithm to improve the accuracy of the heading angle calculation. Second, we designed an extended Kalman filter (EKF) to reduce the cumulative error based on MEMS sensor positioning and large errors based on WiFi fingerprint recognition. Finally, in order to achieve 3D positioning in multi-layer scenes, a calculation algorithm based on floor height is proposed.

The rest of this paper is organized as follows. The second part introduces the integrated WiFi/PDR positioning algorithm and the high degree of calculation method. In the third part we integrated the data from wifi fingerprinting and MEMS sensors to verify our algorithm in a multi-layer scenario. In the fourth part, the experimental conclusions are utilized in the 3D indoor localization WiFi/PDR integrated system.

2 System Description

As shown in Fig. 1, the WiFi/PDR fusion multi-floor 3D positioning algorithm mainly includes four parts: the WiFi fingerprinting positioning, the PDR part, where speed and heading where determined, the EKF part, and the height calculation part. Firstly, we obtained WiFi fingerprinting based positioning, then the speed and heading information of the pedestrian were calculated through the measurement information obtained by the MEMS sensors, and then the combined data was used as the input of the Extended Kalman Filter (EKF). In the fourth step, the height information measured by the barometer. Finally, we got the 3D positioning result of the pedestrian.

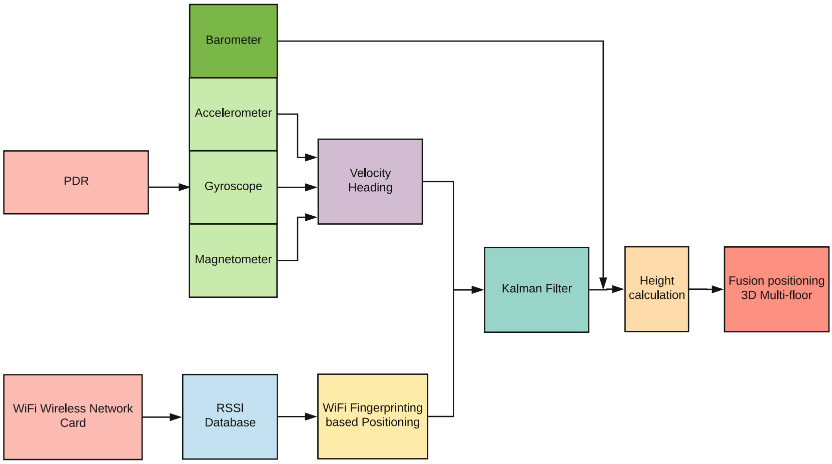

Fig. 1. System scheme.

2.1 WiFi Fingerprinting-Based Positioning

The indoor fingerprinting technology based on location fingerprint mainly includes two stages: offline phase and online phase. In offline phase, the location information and corresponding signals, such as RSSI, AOA, TOA, etc., are collected at the reference point (RP) of the target area. Then we calculate the distribution corresponding to the signals received by different RPs, and then construct an offline location fingerprint database. In online phase, the signals are collected in real time in the target area and the distribution of real-time signals is calculated, and then we compare it with the fingerprint database to find the target location. The best match RP is regarded as the estimated target position.

This paper uses the k-nearest neighbor (KNN) algorithm for localization. The KNN algorithm is a basic classification and regression method. For a training set, input new data, and find k data nearest to the data in the training set. If most of the k data belong to a certain class, the data belongs to this class.

The signal information received by the ith RP can be denoted as [20]

$$\mathbf{T}_i = \begin{bmatrix} \Pr(A_1O_1|\ Pt_i) & \Pr(A_2O_1|\ Pt_i) & \cdots & \Pr(A_nO_1|\ Pt_i) \\ \Pr(A_1O_2|\ Pt_i) & \Pr(A_2O_2|\ Pt_i) & \cdots & \Pr(A_nO_2|\ Pt_i) \\ \vdots & \vdots & \ddots & \vdots \\ \Pr(A_1O_v|\ Pt_i) & \Pr(A_2O_v|\ Pt_i) & \cdots & \Pr(A_nO_v|\ Pt_i) \end{bmatrix} \tag{1}$$

Where A represents AP information, O represents the value obtained by the RSSI experiment, and Pt represents the position information of the RP. The mathematical expectation of the signal strength from each AP is calculated in the RP. The experimental results were utilized to build the required fingerprint database. The fingerprint for the ith RP can be expressed as:

$$\mathbf{T}_i = \left[\bar{\mathbf{S}}_i | Pt_i\right] = \left[\,\Pr(A_1\bar{O})\,\Pr(A_2\bar{O})\cdots\Pr(A_n\bar{O})|Pt_i\,\right] \tag{2}$$

If the WiFi signal strength detected by the mobile device of the user under test is $\mathbf{S}$, hen the distance between the current WiFi signal location feature parameters and the fingerprint database can be calculated by the following matching algorithm.

$$d_i = \left\|\mathbf{S} - \bar{\mathbf{S}}_i\right\| \tag{3}$$

Using the K-nearest neighbors algorithm, the K smallest values of d_i are used to compute the coordinates of the target point by

$$\bar{L} = \sum_{i \in \mathbf{C}} \frac{L_i}{d_i} \tag{4}$$

where $\mathbf{C}$ is the set made up by the K smallest values of d_i and L_i means the coordinates of RP.

2.2 PDR (Pedestrian Dead Reckoning)

PDR (Pedestrian Dead Reckoning) positioning algorithm is a relative positioning algorithm. The basic principle of the PDR positioning algorithm is to use inertial sensors and magnetometers to measure the acceleration, angular velocity, and other information of pedestrian movement, so as to calculate the direction and distance of the pedestrian movement, and together with the known pedestrian position information from the previous moment, to calculate the present moment pedestrians location information. Therefore, when the pedestrian's initial position is known, the pedestrian's position information can be calculated continuously in real time. The basic principle is shown in the Fig. 2.

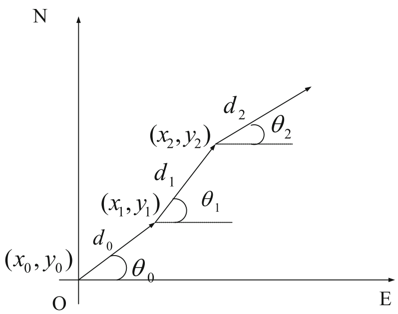

Fig. 2. Illustration of walking path.

If the position of the pedestrian at the initial time t1 is known (x_0, y_0), the initial heading angle θ_0 is the distance measured by the inertial sensor d_0, and the position of the pedestrian at the moment (x_1, y_1) can be calculated as

$$\begin{cases} x_1 = x_0 + d_0 \cos\theta_0 \\ y_1 = y_0 + d_0 \sin\theta_0 \end{cases} \tag{5}$$

In the same way, the position of the pedestrian (x_1, y_1) at the moment t_1 can be calculated by using the heading angle and the position (x_2, y_2) of the moment t_2 as

$$\begin{cases} x_2 = x_1 + d_1 \cos\theta_1 = x_0 + d_0 \cos\theta_0 + d_1 \cos\theta_1 \\ y_2 = y_1 + d_1 \sin\theta_1 = y_0 + d_0 \sin\theta_0 + d_1 \sin\theta_1 \end{cases} \tag{6}$$

According to this calculation, we can calculate the position (x_k, y_k) at the moment t_k by

$$\begin{aligned} x_k &= x_0 + \sum_{i=0}^{k-1} d_i \cos\theta_i \\ y_k &= y_0 + \sum_{i=0}^{k-1} d_i \sin\theta_i \end{aligned} \tag{7}$$

In the formula, d_i it is the time t_{i-1} to t_i forward displacement, which is the heading θ_i of the pedestrian position at the time of i.

2.3 Extended Kalman Filter

When the WiFi signal is in an available state, the time update and the observation update are generally performed in the WiFi/PDR integrated system by using a Kalman filter to complete the state parameter, thereby reducing the estimation error. The time update process is expressed as

$$\begin{aligned} \bar{\mathbf{X}}_i &= \mathbf{F}_{k,k-1}\hat{\mathbf{X}}_{k-1} \\ \bar{\mathbf{P}}_k &= \mathbf{F}_{k,k-1}\mathbf{P}_{k-1}\mathbf{F}_{k,k-1}^T + \mathbf{Q}_{k-1} \end{aligned} \tag{8}$$

In addition, the Kalman filter observation update equation is written by

$$\begin{aligned} \bar{\mathbf{V}}_k &= \mathbf{Z}_k - \mathbf{H}_k\bar{\mathbf{X}}_k \\ \mathbf{P}_{\bar{V}_k} &= \mathbf{H}_k\bar{\mathbf{P}}_k\mathbf{H}_k^T + \mathbf{R}_k \\ \mathbf{G}_k &= \bar{\mathbf{P}}_k\mathbf{H}_k^T\mathbf{P}_{\bar{\mathbf{V}}_k}^{-1} \\ \hat{\mathbf{X}}_k &= \bar{\mathbf{X}}_k + \mathbf{G}_k\bar{\mathbf{V}}_k \\ \mathbf{P}_k &= (\mathbf{I} - \mathbf{G}_k\mathbf{H}_k)\bar{\mathbf{P}}_k \end{aligned} \tag{9}$$

where $\bar{\mathbf{X}}_k$ is the prior probability estimate, $\hat{\mathbf{X}}_k$ is the posterior information estimate, $\mathbf{G}_k$ is the gain matrix of the Kalman filter, $\bar{\mathbf{P}}_k$ is the covariance matrix of prior probability State vector, $\mathbf{P}_k$ is the posterior probability covariance matrix of the state vector, $\mathbf{R}_k$ is the covariance matrix of the observation noise vector, and $\mathbf{Q}_{k-1}$ is the covariance matrix of the process noise. The subscript k denotes the time, and the subscript k, $k-1$ represents the forward positional feature or covariate interference estimate from $k-1$ to k.

2.4 Altitude Calculation

Under normal circumstances, pedestrians are divided into three types: walking on flat roads, climbing stairs and descending the stairs. In these three cases, the method of solving two-dimensional positions is the same. Only a small difference in the size of the specified step, i.e., the step length should be set to the width of the stair step.

This article uses only the altitude value measured by the barometer to judge the upper and lower levels, and the actual height information is calculated by estimating the height from the floor. Pedestrians can be divided into two types of situations: (1) walking on the floor; (2) climbing the stairs or going down the stairs.

3 Experimental Results

The tests were carried on the first and second floors in a building of a university. The floors plan is described in Fig. 3, the first floor dimensions are $64.6 \times 18.5\,\mathrm{m}^2$ and second floor are $81.2 \times 18.5\,\mathrm{m}^2$. 10 D-Link DAP 2310 APs (marked in red) are disposed in this scenario, named AP_1, AP_2, AP_3, AP_4, AP_5, AP_6, AP_7, AP_8, AP_9, and AP_{10}. The RPs are evenly regulated with an spacing of 0.6 m.

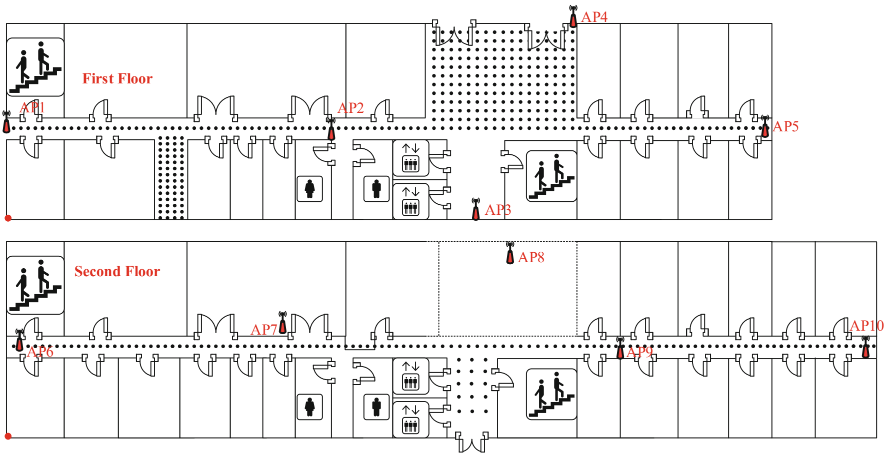

Fig. 3. Floor plan. (Color figure online)

In our experiment, the smartphone Samsung Galaxy S3 was selected as the receiver, which integrates an accelerometer, gyroscope, magnetometer, barometer, and WiFi module. We used two applications, Wifi sensors and Wifi localization for MEMS sensors and WiFi RSSI measurements. Measured data is stored on a Secure Digital (SD) card and the recording frequency is equivalent to 50 Hz. Figure 4 shows the WiFi AP and the mobile phone for test.

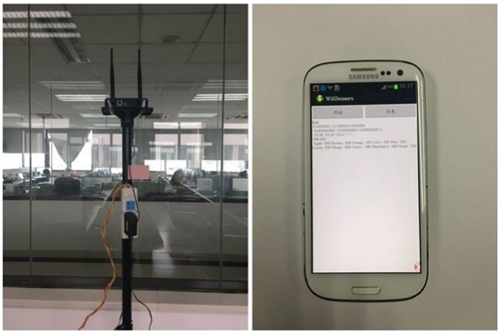

Fig. 4. WiFi AP and mobile phone for test.

Figure 5 shows the real path and positioning results of the test node. In the 3D plan, the estimated path is displayed utilizing PDR (traditional MEMS sensor-based localization method [16] and WiFi fingerprint-based localization method [4]) and the proposed integrated WiFi/PDR positioning method. The measurements indicate that the proposed method effectively reduces the errors which accumulated in the PDR, thus significantly improves the 3D positioning work in a multi-tier scenario compared to a separate WiFi and PDR system.

By adopting the proposed height work-out method, the traditional height calculation method based on barometer [21], the height work-out method based on K-means [22], the height estimation error cumulative distribution function (CDF)/PDR against PDR and WiFi, respectively Compare in Fig. 6. As can be seen from Figs. 5 and 6, the result of the calculation method based on the barometer height is not stable, and when the test node is located in the stairway, the efficiency of the height work-out method based on the K value is seriously deteriorated.

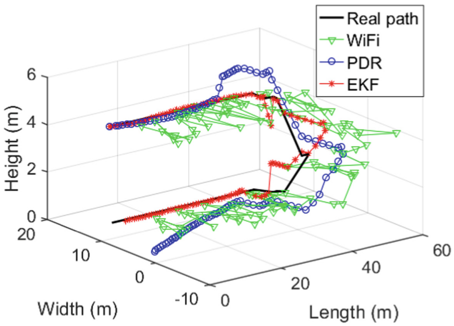

Fig. 5. Localization results.

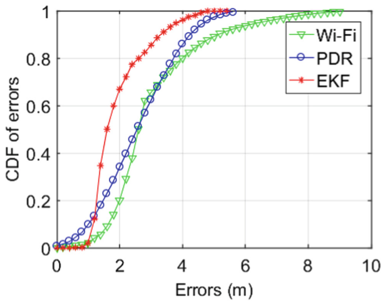

Fig. 6. CDF of localization error.

Errors of CDFs for 3D localization using PDR and WiFi/PDR integrated systems using WiFi with Kalman filter method is also included in Table 1. As depected in Table 1, we can see that the proposed method gets an average positioning error of 1.6 m and a 90% error is less than 3.4 m, which is much more precise than the performance of traditional Wi-Fi-based and PDR-based methods.

Table 1. Comparison of algorithm performance

	Largest positioning error (m)	Mean positioning error (m)	67% positioning error (m)	90% positioning error (m)
Wi-Fi	9	2.6	2	5.2
PDR	5.6	2.6	3.2	4.2
EKF	5.4	1.6	2	3.4

4 Conclusion

In this paper, we propose a innovative smartphone-based indoor WiFi/PDR multi-layer location algorithm to locate a multi-layer environment in 3D. Experimental results indicate that our method can reduce the errors accumulated by the localization based on PDR sensors and the significant errors of WiFi Fingerprint-based localization. Compared with traditional PDR sensor-based localization and WiFi fingerprint-based localization methods, our method achieves higher accuracy measurements with an average localization error of 1.6 m and a 90% 3D positioning error of less than 3.4 m. In addition, for our future work we can adapt our system to different users by changing the step size.

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