Chapter 63
Wi-Fi Fingerprint Positioning Updated by Pedestrian Dead Reckoning for Mobile Phone Indoor Localization

Qiang Chang, Samuel Van de Velde, Weiping Wang, Qun Li, Hongtao Hou and Steendam Heidi

Abstract The widespread deployment of Wi-Fi communication makes it easy to find Wi-Fi access points in the indoor environment, which enables us to use them for Wi-Fi fingerprint positioning. Although much research is devoted to this topic in the literature, the practical implementation of Wi-Fi based localization is hampered by the variations of the received signal strength (RSS) due to e.g. impediments in the channel, decreasing the positioning accuracy. In order to improve this accuracy, we integrate Pedestrian Dead Reckoning (PDR) with Wi-Fi fingerprinting: the movement distance and walking direction, obtained with the PDR algorithm, are combined with the K-Weighted Nearest Node (KWNN) algorithm to assist in selecting reference points (RPs) closer to the actual position. To illustrate and evaluate our algorithm, we collected the RSS values from 8 Wi-Fi access points inside a building to create a fingerprint database. Simulation results showed that, compared to the conventional KWNN algorithm, the positioning algorithm is improved with 17 %, corresponding to an average positioning error of 1.58 m for the proposed algorithm, while an accuracy of 1.91 m was obtained with the KWNN algorithm. The advantage of the proposed algorithm is that not only the existing Wi-Fi infrastructure and fingerprint database can be used without modification, but also that a standard mobile phone is sufficient to implement our algorithm.

Keywords Indoor localization · Wi-Fi fingerprint · K-Weighted nearest node algorithm · Pedestrian dead reckoning algorithm

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63.1 Introduction

Acquiring accurate location information is essential for many applications. Therefore, researchers developed several algorithms to estimate a user's position. Among the solutions, the most popular system is the Global Navigation Satellite System (GNSS), which includes GPS, Galileo and Beidou. Because of the accuracy of GNSS, i.e., normally the average positioning error is 3–10 m, GNSS is widely used for outdoor navigation. On the other hand, with the arrival of the era of mobile Internet, Location Based Service (LBS) developed dramatically: the need of indoor positioning has increased rapidly. However, the indoor environment severely degrades the accuracy of GNSS positioning or makes it totally impossible. As a result, several alternative positioning techniques for indoor positioning were proposed. Some of them are based on the GNSS, such as AGNSS (Assisted GNSS) or DGNSS (Difference GNSS), but most of them rely on other approaches, such as Wireless Sensor Networks (WSNs), cameras, Wi-Fi radio fingerprinting or inertial measurement units (IMUs). In general, all above mentioned algorithms have their strengths and weaknesses, when comparing them with respect to accuracy, complexity and deployment costs. As a result, there still no well-performing positioning technique for indoor localization exists.

Among the solutions for indoor positioning, the Wi-Fi fingerprinting technique has received much attention because Wi-Fi access points are already widely available, implying the deployment costs are negligible compared to other solutions, and some commercial products are already developed, such as google maps, WiFiSlam or Rtmap. Because of the weak relationship between the RSS and the position of the user, a Wi-Fi fingerprinting positioning algorithm consists of two phases: training and localization. First, during the training phase, Received Signal Strength (RSS) samples from the Access Points (APs) are collected and stored in a database together with their location coordinates. Next, in the localization phase, a user's current position is estimated based on the comparison of the measured RSS and those stored in the database. The requirement of an accurate database is the weak point of this technique: because of the Wi-Fi variance problem [1], which is caused by differences in the used device type, the user's direction, measurement time and environmental changes between the two phases, the estimation error is 10 m or even worse, such that the database must be updated regularly. The large estimation error in an outdated database is mainly caused by the selection of irrelevant reference points (RP) that are far from the actual position of the user.

A second widely used indoor positioning technique is Pedestrian Dead Reckoning (PDR) [2], based on information obtained from IMUs. In this technique, raw data from e.g. an accelerometer, a compass and a gyroscope is fused to estimate a user's trajectory. A major advantage of this technique is that no infrastructure is needed to estimate the relative trajectory of a user, although additional fixed anchors are required to find the absolute position of the user.

Both PDR and Wi-Fi fingerprint positioning have their strengths and weaknesses. The PDR algorithm has the advantage of high availability, and immunity to external environment changes, but the downside of this technique is that it suffers from a drift error that increases with time: e.g., [2] reports a position offset after a 1 km walk of about 10 m, but short term results are accurate. In contrast to the PDR system, the positioning accuracy of the Wi-Fi fingerprinting positioning technique is reasonably low, even on the long term, but susceptible to external disturbances which lead to erratic, but bounded localization errors. Due to the complementary error behaviour, the combination of these two algorithms is expected to have better performance than the two single algorithms. In this paper, we integrate Pedestrian Dead Reckoning (PDR) with Wi-Fi fingerprinting to provide an accurate positioning algorithm. The short term moving distance and walking direction from PDR are applied to assist the KWNN algorithm to select reference points closer to the actual position, so that the positioning accuracy is improved. Hence, the proposed algorithm offers a solution to the RSS variance problem and the aging of the database, as the outdated database still can be used. Therefore, our algorithm reduces the maintenance cost of the system as the database should be updated less regularly.

63.2 Related Works

There is a vast literature on hybrid positioning techniques, combining two or more approaches to estimate a user's position. By combining measurements from different sources, researchers attempt to improve the accuracy of a single approach. Hence, the combination of Wi-Fi fingerprinting and IMU has been considered earlier.

For example, Xiao [3] developed a stochastic system model based on a finite state machine that utilizes the Wi-Fi fingerprint position estimates as its measurements, and the inertial sensing data as control inputs to track the target's position. Although this algorithm improves the positioning accuracy, it comes at the cost of a high computational complexity. A similar approach was used by Korbinian [4] to fuse data from the IMU and the Wi-Fi fingerprint algorithm. However, Korbinian considered shoe mounted IMU devices, such that the practical use for daily life is limited. Both approaches [3] and [4] considered Kalman filters for combining the results, but other types of filters, such as a particle filter [5] are also being considered: HiMLoc [6] combines location tracking and activity recognition using inertial sensors and Wi-Fi fingerprinting via a particle filter. However, HiMLoc requires the knowledge of a basic map including locations of stairs, elevators, corners and entrances. The IMU and Wi-Fi fingerprint based algorithm 'Zee' [7] also needs a map showing the pathways and barriers. Berkovich [8] develops a navigation engine that combines the measurements from a 3D accelerometer, a gyroscope, a magnetometer, Wi-Fi and BLE modules, together with a floor map. The real-time indoor positioning accuracy of the engine is about 1–2 m, but this algorithm is high energy consuming. Herrera [9] creates an indoor positioning algorithm using a particle filter to combine PDR, beacon-based Weighted Centroid position estimates, map information from OpenStreetMap and a users path density map. This high-energy-consuming algorithm obtains an average accuracy of 2.48 m. Chai [10] presents a PDR/Wi-Fi/barometer integrated system, where an adaptive Kalman filter is employed for sensor fusion. As a barometer is not always available to the users, the practical use of the algorithm is limited. In [11], Jin presents a nearest-neighbor selection algorithm for real-time Wi-Fi fingerprint positioning with the assist of inertial measurement unit (IMU) measurements. The algorithm first selects several RPs according to the conventional KWNN algorithm. Then, filtering out irrelevant reference points based on the position prediction with IMU measurements.

Comparing with the current literature, we combine the results on a much lower level, i.e., we incorporate the movement distance and walking direction directly in the KWNN algorithm. Further, the sensors that are used in our algorithm are a gyroscope and an accelerometer, which are readily available in standard mobile phones. Our algorithm has a very low complexity, especially compared to a particle filter, and requires no assumptions about a noise model. This is in contrast with both the Kalman and particle filters, which both need the knowledge of the noise parameters.

63.3 System Description

63.3.1 Algorithm Framework

The architecture of the proposed algorithm is given in Fig. 63.1. The algorithm contains three stages: sensor measurement, PDR calculation, and KWNN localization.

In the measurement phase, the algorithm records the internal sensor readings of the mobile phone, which is equipped with an accelerometer, a gyroscope, and a Wi-Fi card. We use the Wi-Fi card to obtain the APs' Radio Signal Strength, the gyroscope to measure rotational forces along the device's three axes, and the accelerometer to measure the acceleration of the device. The digital compass, which is also available in the device, is not used in this algorithm, as it is easily affected by external magnetic fields and operating electronic devices, resulting in non-reliable measurements. In the PDR calculation phase, the readings of the accelerometer and gyroscope are fused to detect the number of steps and walking direction. Based on the number of steps and direction, an estimate of the user's coordinates can be determined. In the last phase, the KWNN algorithm is performed after every m steps, m = 1, 2,…. By reducing the number of KWNN executions, i.e., by increasing m, the location server's computation load is reduced and the mobile phone's battery life is prolonged.

A detailed description of the PDR and KWNN algorithm is given in the following sections.

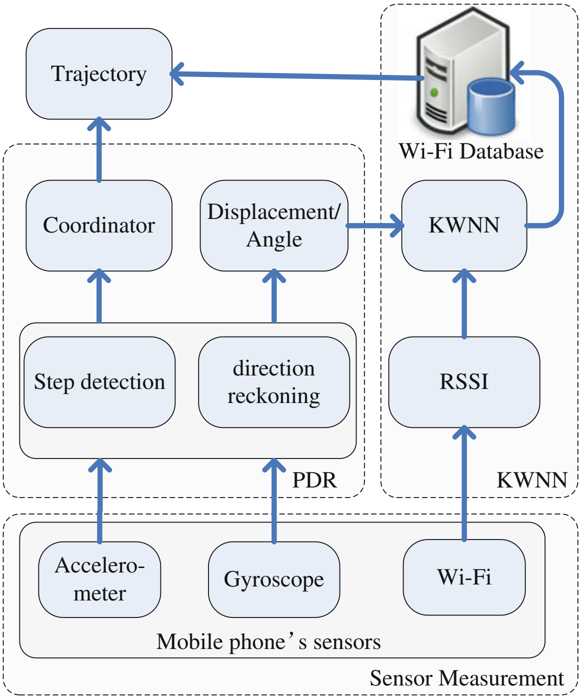


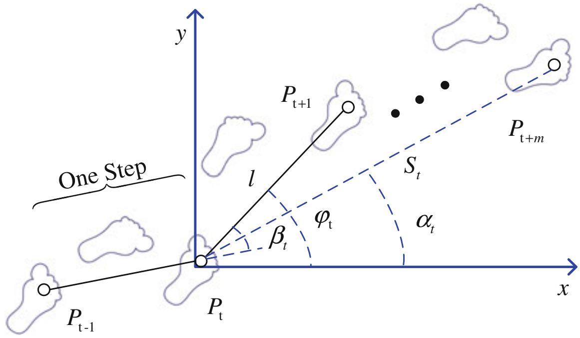
Fig. 63.1 Architecture of the proposed algorithm

63.3.2 PDR Algorithm

In the PDR algorithm, the readings of the accelerometer and gyroscope are fused to detect the user's number of steps and walking direction. The process of the step counting is out of the scope of this paper and will not be discussed. The walking direction is estimated by integrating the previous location, and the readings of the gyroscope and the accelerometer. Based on the number of steps and direction, the coordinates (x, y), moving distance S_t and turning angle α_t can be determined (see Fig. 63.2). We define a step in our algorithm as two actual footsteps, one of both feet, i.e., from a step from the right (or left) foot to the next step from the right (or left) foot. In this paper, P_t refers to the true position of the user at time t, $P_t = \{x_t, y_t\}$, and $P_{\mathrm{t,PDR}}$ and $P_{\mathrm{t,WiFi}}$ are the positioning results from the PDR and the Wi-Fi fingerprint algorithm at time t, respectively.

Assuming that we have the position estimate from the Wi-Fi fingerprint algorithm at time t, i.e. $P_{\mathrm{t,WiFi}}$, we can estimate the locations in the next m steps with the PDR algorithm:

Fig. 63.2 PDR algorithm



$$\begin{cases} x_{t+\mathrm{k,PDR}} = x_{\mathrm{t,WiFi}} + \sum_{i=1}^{k} l \cos \varphi_{t+k-1} \\ y_{t+\mathrm{k,PDR}} = y_{\mathrm{t,WiFi}} + \sum_{i=1}^{k} l \sin \varphi_{t+k-1} \end{cases}, k = 1, 2, \ldots, m \tag{63.1}$$

In Eq. 63.1, l is the step length and φ is the walking direction as illustrated in Fig. 63.2. The angle φ_t can be calculated as follows:

$$\varphi_t = \begin{cases} \varphi_{t-1} + \beta_{\mathrm{t}}, & t > 0 \\ 0, & t = 0 \end{cases} \tag{63.2}$$

After m steps, the moving distance S_t and turning angle α_t yield:

$$\begin{cases} S_t = \left\| P_{\mathrm{t+m,PDR}} - P_{\mathrm{t,WiFi}} \right\| \\ \alpha_t = \arctan \frac{y_{\mathrm{t+m,PDR}} - y_{\mathrm{t,PDR}}}{x_{\mathrm{t+m,PDR}} - x_{\mathrm{t,PDR}}} \end{cases} \tag{63.3}$$

where $\|\bullet\|$ is the Euclidean distance.

In Eq. 63.1, we have introduced a fixed step length l to compute the coordinates with the PDR algorithm. Note that, in reality, the step length l not only varies from person to person, but also for a single person the step length is not the same all the time. Nevertheless, it is observed that on short term, in general, the step length of a person will not change significantly. Therefore, we can update the step length based on the historic walking data.

$$l_t = \frac{\left\| P_{\mathrm{t-m,WiFi}} - P_{\mathrm{t,WiFi}} \right\|}{\sqrt{\left(\sum_{i=1}^{m} \cos \varphi_{k-m+i}\right)^2 + \left(\sum_{i=1}^{m} \sin \varphi_{k-m+i}\right)^2}} \tag{63.4}$$

In the following, for notational convenience, we drop the dependency of the step length on the time index.

63.3.3 KWNN Based Wi-Fi Fingerprint Algorithm

Many algorithms can be used to estimate the user's position based on the RSS measurements and the available database. In this paper, we adopt the K Weighted Nearest Neighbor (KWNN) Wi-Fi fingerprint positioning algorithm. In this algorithm, to estimate the position, the K nearest neighbor reference points (RPs) are selected based on the RSS signal distance, i.e., the difference between the measured RSS and the RSS values available in the database. With this algorithm, the coordinates are calculated as:

$$P_{\mathrm{t+m,WiFi}} = \left\{ \sum_{i=1}^{k} x_{\mathrm{DB},i} w_i, \sum_{i=1}^{k} y_{DB,i} w_i \right\} \tag{63.5}$$

where $(x_{DB,i}, y_{DB,i})$ are the coordinates of RP i, and the weight w_i is defined as:

$$w_i = \frac{1/\varepsilon_{DIS,i}^{p}}{\sum_{j=1}^{k} 1/\varepsilon_{DIS,i}^{p}} \tag{63.6}$$

In Eq. 63.6, $\varepsilon_{DIS,i}$ is the RSS signal distance and p is a parameter that can be changed to optimize the positioning accuracy.

In the standard KWNN algorithm, $\varepsilon_{DIS,i}$ is determined by the difference between the RSS values available in the database and the measured RSS value between the user. Because of signal blocking, the RSS values of the nearest reference points can differ significantly from the measured RSS value. This can be illustrated by Fig. 63.3. The nearest 4 reference points, selected by the conventional KWNN algorithm, are not the best ones due to the RSS variance problem. In order to improve the estimation accuracy, we include information obtained from the PDR algorithm in the expression for the error distance $\varepsilon_{DIS,i}$. Note that these two parameters are both acquired on short term only, to avoid the error accumulation in the PDR step. Using this distance definition, the KWNN algorithm is able to select the most relevant RPs, as illustrated in Fig. 63.3.

With the PDR algorithm, we are able to calculate the moving distance and turning angle between two Wi-Fi fingerprint estimations. We include these in the error distance $\varepsilon_{DIS,i}$ as follows:

$$\varepsilon_{\mathrm{DIS},i} = D_{RSS,i} + \lambda D_{LOC,i} + \gamma D_{AGL,i} \tag{63.7}$$

where $D_{RSS,i}$ is the signal distance from the standard KWNN algorithm:

$$D_{RSS,i} = \left(\sum_{j=1}^{n} RSSI_{DBi,j} - RSSI_{MR,j}|^{q} \right)^{1/q} \tag{63.8}$$

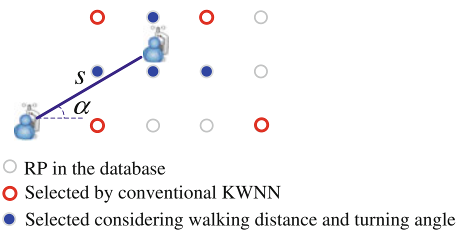


Fig. 63.3 PDR assisted RP selection

n is the number of access points (APs), $RSSI_{DBi,j}$ is the RSS value from the database for AP j, measured in RP i, $RSSI_{MR,j}$ is the RSS value measured by the user, and the parameter q can be changed in order to optimize the accuracy.

The location distance $D_{LOC,i}$ is the location distance:

$$D_{LOC,i} = \left| \left\| P_{DB,i} - P_{\mathrm{t,WiFi}} \right\| - S \right|^q \tag{63.9}$$

where $P_{DB,i}$ is the coordinate of RP i, and $P_{\mathrm{t,WiFi}}$ is the coordinate of the previous Wi-Fi fingerprint position estimate. Finally, the angular distance $D_{\mathrm{AGL,i}}$ is given by:

$$D_{AGL,i} = \left| \left(\arctan \frac{y_{DB,i} - y_{t,WiFi}}{x_{DB,i} - x_{t,WiFi}} - \alpha_t \right) \%180 \right|^q \tag{63.10}$$

The location distance $D_{LOC,i}$ and the angular distance $D_{\mathrm{AGL,i}}$ in Eq. 63.7 are added to the error distance with the weighting factors λ and γ, which can be selected to optimize the performance.

63.4 Performance Analyses

To evaluate the proposed algorithm, we have created a 3D model of an office environment covering a total area of over 900 m^2. Eight APs are present in this environment. The radio map for each AP is computed by means of 3D ray tracing.[1] The floor plan of the office area and the coordinates of the APs are shown in Fig. 63.4.

Figure 63.5 shows the RSS radio map for AP 1.

In our simulation setup, we created from the training data a database with 300 RPs. The obtained radio map, originating from the ray tracing program, is considered as the ground truth, and we use it to generate RSS measurements by adding zero mean Gaussian noise with a standard deviation of 5 dBm. For the step length estimation, we define a step length of 1 m and add 0 mean Gaussian noise with a

[1]We use the WinProp program from AWE Communications for the 3D ray tracing.

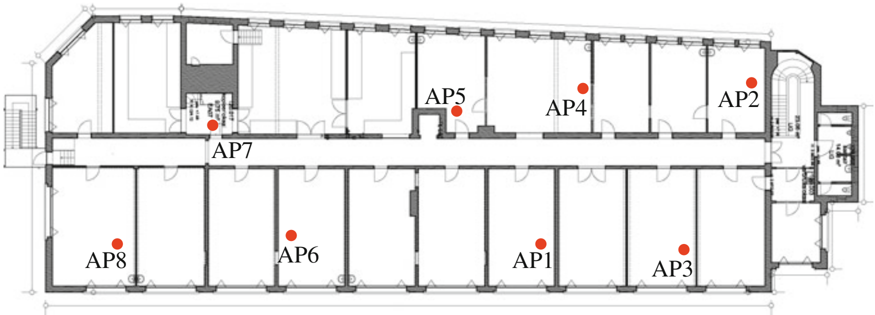


Fig. 63.4 Floor Plan of the indoor environment and the distribution of the APs

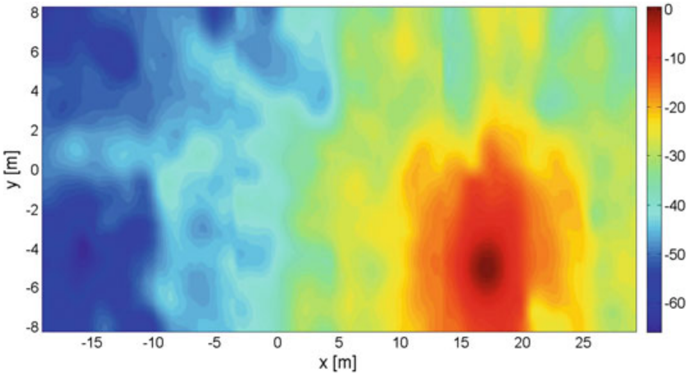


Fig. 63.5 Radio map of AP 1

standard deviation of 0.1 m. The walking direction equals the true direction distorted by zero mean Gaussian noise with a standard deviation of 1 degree. Simulations are performed for 2D localization and the conventional KWNN algorithm is compared with the proposed algorithm. During the simulation, the parameters are selected as follows: $k = 4$, $p = q = 2$, $\lambda = \gamma = 1$, $m = 1$.

The CDF (Cumulative Distribution Function) of the estimation error is shown in Fig. 63.6.

We observe that the new algorithm results in a higher accuracy than the KWNN algorithm: for the proposed algorithm, 80 % of the positioning errors is smaller than 2.05 m, whereas 2.55 m for the KWNN algorithm. Hence, the accuracy is improved with 20 %. Further, the probability of obtaining an error below 2 m is 78 % for the proposed algorithm, as compared to a probability of 59 % for the KWNN algorithm. The average error for the new algorithm is 1.58 m, while 1.91 m for KWNN. Hence, the performance is improved with 17.11 %.

Figure 63.7 shows the RMSE (Root-Mean Square Error) when the number m of steps between two Wi-Fi fingerprinting estimates varies.

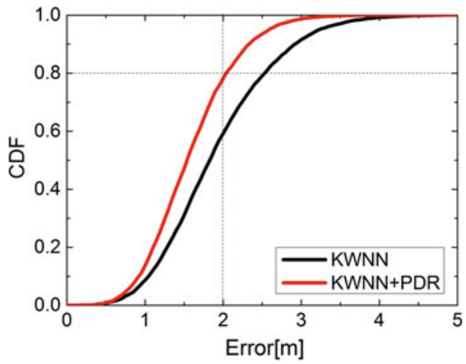


Fig. 63.6 CDF *curve* comparing different algorithms

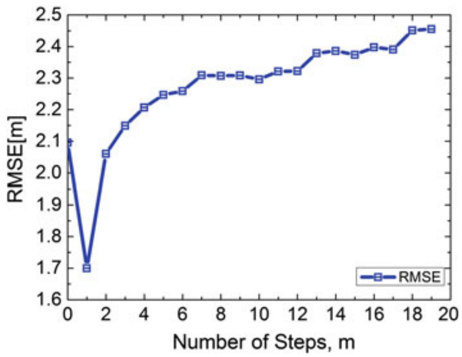


Fig. 63.7 RMSE *curve* of different number of steps

From Fig. 63.7, it follows that the minimum RMSE is achieved when the number m of steps equals 1, and when m increases, the RMSE increases. This can be explained as the accuracy of the PDR algorithm degrades when the number of steps grows. Hence, although the battery life of the mobile phone benefits from reducing the number of KWNN executions, the location error increases as a result. Nevertheless, our simulation results show that the resulting RMSE is only slightly larger than the RMSE of the conventional KWNN algorithm, even if the number of steps is increased. Hence, to reduce the power consumption of the positioning algorithm, the proposed algorithm offers a solid solution.

63.5 Conclusions and Future Work

In this paper, we propose a novel indoor positioning algorithm based on Wi-Fi fingerprint and PDR. The moving distance and walking direction from the PDR are used to assist the KWNN algorithm to select the most relevant RPs. Extensive simulations demonstrate that the proposed algorithm provides more accurate position estimates than the KWNN-based Wi-Fi fingerprinting positioning algorithm, if in every step the RSS is measured. Further, we can reduce the complexity of the algorithm by considering RSS measurements only after m steps, by using the information of the PDR algorithm, without significantly degrading the performance. Our algorithm has very low complexity, especially as compared to a particle filter used as in [5], and offers the same accuracy. Moreover, no knowledge about the noise model is required. The existing Wi-Fi infrastructure and fingerprint database can be used without modification, and a standard mobile phone is sufficient to implement our algorithm.

In the future, the parameters of the algorithm (p, q, λ and γ) should be optimized such that the average positioning error is minimized. Further, real-life measurements should be conducted to test the algorithm.

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