THE DEPLOYMENT OF A Wi-Fi POSITIONING SYSTEM VIA CROWDSOURCING

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Commission III, WG III/1

KEY WORDS: Wi-Fi fingerprint indoor positioning, morphology similarity distance, device heterogeneity, outlier detection, combined weight.

ABSTRACT:

Wi-Fi fingerprint positioning is widely used because of its ready hardware and high accuracy. However, its application is considerably restricted by time-consuming and labor-intensive works of offline collection and irregular fluctuation of signals. To address the above problems, we proposed a novel method to deploy the Wi-Fi fingerprint database based on implicit crowdsourcing and improved the weighted k-nearest neighbor (WKNN) algorithm to eliminate the influence of neighbor mismatching and device heterogeneity. First, ordinary users continuously gather Wi-Fi information instead of collecting one point after another. Meanwhile, video surveillance cameras record users' trajectories without any intervention and use monocular vision based on plane constraints to obtain users' location at the moment of each scanning. At the localization phase, the morphology similarity distance instead of the Euclidean distance is used to measure the similarity of signals to solve the problem of device heterogeneity. Outlier detection is also utilized for a secondary selection of neighbor points. Finally, geometric and signal morphology similarity distances are used to determine the combined weight of all neighbors after the dimensionless treatment. Results of the experiments conducted in a real indoor environment show that the proposed strategy improves the efficiency of fingerprint collection and achieves higher positioning accuracy.

1. INTRODUCTION

The outdoor location service has increasingly matured with the rapid development of the global navigation satellite systems (GNSS). However, GNSS fails to provide indoor positioning service due to signal obstruction and attenuation. On the contrary, indoor positioning is becoming important in people's daily activities, such as shopping, parking, and health monitoring. Accordingly, many local and international scholars have conducted considerable research on indoor positioning. Numerous techniques have been proposed, such as Bluetooth(Zhou and Pollard 2006), geomagnetic localization(Subbu, et al. 2011), radio frequency identification (RFID)(Liu and Zhong 2018), ultra-wideband(Zapater and Kyamakya 2003), wireless local area network, computer vision(Wu, et al. 2017), visible light positioning(Lee, et al. 2012), and pedestrian dead reckoning (PDR) assisted by the accelerator and gyroscope(Kang and Han 2015).

In this study, we mainly deal with the following challenges in Wi-Fi fingerprint positioning. The first and foremost challenge in deploying a Wi-Fi positioning system is building and updating the fingerprint database. At present, two main methods can be used to construct the fingerprint database: manually collecting received signal strength (RSS) samples on each reference point and crowdsourcing. Each method has its own strengths and weaknesses. The manual collection has higher accuracy than crowdsourcing. Although the density of fingerprint points considerably influences the localization accuracy of both methods, the former may be a more time-consuming and laborious process than the latter. Some scholars have even introduced the influence of direction into fingerprint point collection by collecting RSS data from all directions to reduce the influence of the human body(Bi, et al. 2018). Signal attenuation and change in environment require updating the fingerprint database constantly. These steps certainly increase the workload. Crowdsourcing improves data collection but cannot guarantee the quality of the collected data. This method faces the problem of device heterogeneity and the influence of varying signal environments. Signal fluctuation, which leads to mismatching during the selection of neighbor points, is another concern of this research. Averaging and filtering are two other common approaches used for access point (AP) selection(Kushki, et al. 2007) to abandon some unstable APs.

The main contributions of this study are summarized as follows. (1) A novel method for constructing a Wi-Fi fingerprint database via implicit crowdsourcing is proposed. Ordinary users continuously collected Wi-Fi information, whereas video cameras recorded users' trajectories without any intervention. Monocular vision based on plane constraints is used to obtain the location of reference points rather than measuring the site and designing the layout of reference points in advance. This technique considerably improves the efficiency of fingerprint collection. (2) An improved WKNN algorithm is proposed, which includes using the morphology similarity distance, secondary selection of neighbors by outlier detection, and weight combination after mapping the geometric and RSS similarity distances to the same range. The procedures are used to eliminate the influence of neighbor mismatching and device heterogeneity.

The rest of the paper is organized as follows. Section 2 lists the work of international and domestic academics in Wi-Fi indoor fingerprint positioning. Section 3 presents the proposed new method that involves two parts: fingerprint database construction via implicit crowdsourcing, and the improved WKNN algorithm. Section 4 provides the conducted experiments and presents the results and brief analyses of these experiments. Section 5 elaborates the conclusions and future works.

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https://doi.org/10.5194/isprs-archives-XLVI-3-W1-2022-7-2022

Domestic and foreign researchers have proposed many solutions to solve the problems in Wi-Fi indoor fingerprint positioning. A popular system called RADAR proposed by the Microsoft research team in 2000(Bahl and Padmanabhan 2000) used manual collection for data acquisition. Subsequently, many indoor positioning systems based on the RADAR prototype have been developed. An example is the Horus system proposed by Youssef (Youssef and Agrawala 2008). They improved the efficiency of fingerprint database construction by keeping a constant speed to achieve continuous collection and used road signs and maps to correct the position of the collector. The system remarkably reduces the labor cost but fails to estimate the position of the fingerprint point accurately. Gunawan (Gunawan, et al. 2012) used RFID to provide precise location coordinates for the collector. RFID improves the accuracy of the position of reference points but requires additional equipment. RFID can be directly used for positioning without superfluous work. Woodman (Woodman and Harle 2009) applied an inertial measurement unit (IMU) on the foot to estimate the position of the collector. Similarly, this method needs additional equipment and exhibits error accumulation. Some restrictions on pedestrian routes and walking manners are also necessary for its operation.

In recent years, many international researchers have proposed methods to ease the work of RSS collection. Zou (Zou, et al. 2017) proposed WinIPS, a Wi-Fi-based non-intrusive IPS that enables automatic online radio map construction and adaptation, and introduced a novel Gaussian-based regression model to approximate the non-uniform RSS distribution of an indoor environment. Similarly, Yang (Yang, et al. 2012) and WU(Wu, et al. 2018) realized the automatic construction of a fingerprint map. These methods depend on the quality of the model, but no ideal model to simulate the signal propagation rule effectively in an indoor environment is available. Others have used crowdsourcing for RSS acquisition. For example, Hossain (Hossain and Soh 2015) and Wu (Wu, et al. 2012) used the data collected by ordinary users to construct a fingerprint database. This method reduces the workload but produces inaccurate positioning results. Zhuang (Zhuang, et al. 2015) propose a method using multi-sensors in the smartphone to automatically generate the Wi-Fi database by crowdsourcing. However, the crowdsourced database has a relatively low location accuracy. Shen (Shen, et al. 2013) featured the changes in Wi-Fi signals during the user's movement and used massive data of RSS to reconstruct the floor plan of the interior. The proposed strategy is suitable for fingerprint database construction.

Some specific problems in Wi-Fi fingerprint localization have also been studied by researchers. The main problem is device heterogeneity. Song (Song and Wang 2017) adopted min–max normalization method to map the RSS values of all points to a uniform range [−1, 1]. This method provides a more useful comparison relationship than the absolute value of signal strength. Hossain (Hossain, et al. 2011) used signal strength difference to examine the results of the k-nearest neighbor(KNN) algorithm and found that using different mobile devices with heterogeneous hardware still achieves high accuracy. Dong (Dong, et al. 2009) presented a calibration-free solution for handling the signal strength variance between diverse devices. The key idea is to generate a radio map using signal strength differences between pairs of APs instead of absolute signal strength values. For device heterogeneity, some solutions are easily affected by a large signal jump, insufficiently reliable, and dependent on the differential equation model. Some parameters have been studied as well. Ozcelik (Özçelik and Dönmez 2017) evaluated the performance of KNN algorithm with different K values. Caso (Caso, et al. 2015) also set dynamic K values to evaluate errors of different positioning algorithms. Chen (Chen, et al. 2014) analyzed the performance of different algorithms with the intensive deployment of APs. The results showed that the performance of different algorithms changes when the number of APs changes. Sweatt (Sweatt, et al. 2015) implemented an AP placement algorithm to achieve single coverage and designed a k-coverage AP placement algorithm for minimizing the total number of APs in indoor positioning.

2. SYSTEM COMPONENTS AND METHODS

2.1 Components of the Proposed Positioning System

Figure 1 shows the proposed positioning system that involves two main phases: offline collection and online positioning. In the offline phase, video surveillance cameras are utilized to record ordinary users' trajectories. Then, the monocular vision based on plane constraint is used to calculate users' coordinates at the moment of each scanning for constructing a fingerprint database rapidly without any intervention. The phase mainly includes camera calibration, moving target detection, and coordinate transformation, which is discussed in the next section in detail. Data collected by users who are at a slow pace are used due to the scan delay. In the positioning phase, an improved WKNN algorithm is proposed. Morphology similarity distance rather than the Euclidean distance is used to select neighbor points for eliminating the influence of device heterogeneity. Then, outlier detection is utilized for the secondary selection of neighbor points. Finally, geometric and signal morphology similarity distances are adopted to determine the combined weight after the dimensionless treatment.

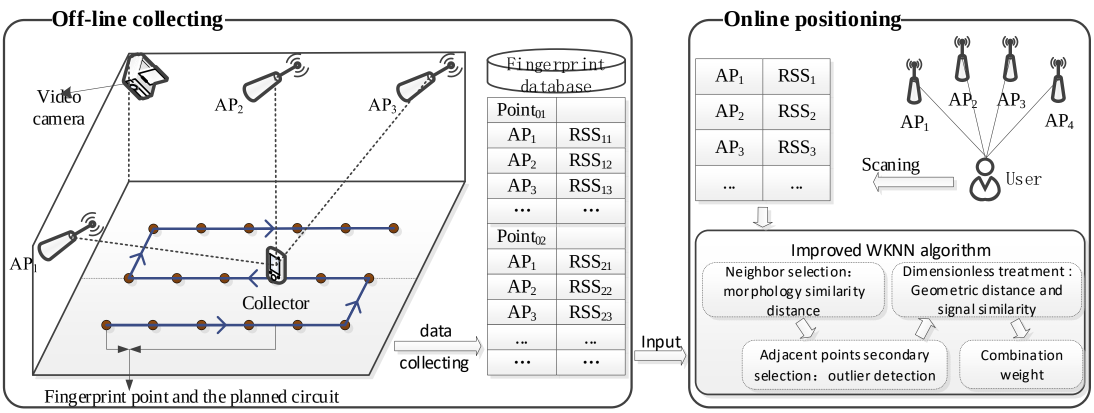


Figure 1. Components of the proposed positioning system.

2.2 Fingerprint Database Construction via Implicit Crowdsourcing

The process of fingerprint database construction via implicit crowdsourcing involves three parts: camera calibration, moving target detection, and coordinate transformation. Figure 2 depicts the entire calculation process of the coordinates of a moving target. First, the calibration method of Zhang(Zhang and intelligence 2000) is used to acquire the extrinsic and intrinsic parameter matrixes of the camera and other parameters. Then, the moving target is detected in the picture extracted from video sequences to output the average pixel coordinates of the target. Finally, the rotation matrix and pixel coordinates are used to calculate the target's coordinates in the world coordinate system.

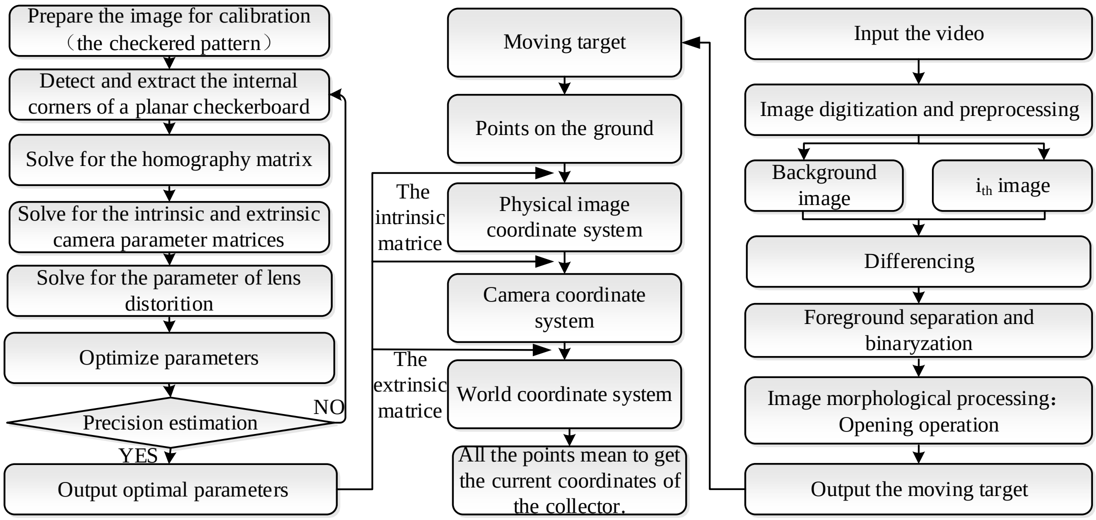


Figure 2. Calculation process of the coordinates of a moving target.

2.3 Unifying the Times of Camera and Device

Video surveillance cameras are used to record users' trajectories. The devices held by users collect RSS information at the same time. The times of the camera and the device are unified to ensure that the location of users acquired by the video sequence corresponds to the RSS information. The time difference between the moment of mutation of the device location detected by the camera and the moment of a sudden change in the data acquired by the built-in sensor of the device is used to map these times to the same benchmark.

The frame difference method is used to detect the moment of device movement. A gray change will appear when the location of the device changes. The difference in adjacent frame pictures is obtained. If the difference is beyond the threshold range, then the position of the device starts to change. The time of position changing can be obtained by combining the video start time and the frame rate. The change in the built-in sensor of the device can also be obtained. We can obtain another time of device position change by comparing the time differences between the device for collection and the video camera. The whole process is depicted in Figure 3.

$$\Delta I(x, y) = |I_t(x, y) - I_{t-1}(x, y)| \quad (1)$$

where $I_t(x, y)$ represents the value of an image at time t; $I_{t-1}(x, y)$ represents the value of an image at time t-1. If $\Delta I(x, y)$ is approximately equal to 0 or is a small value, then the position of the device is not changed.

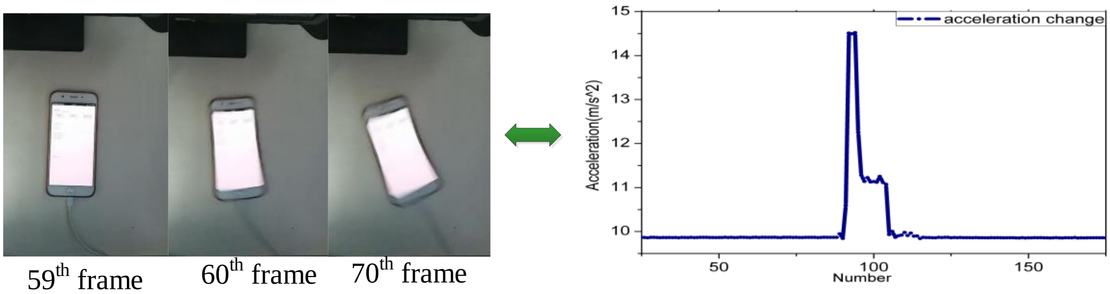


Figure 3. Time relationship between the device and video surveillance camera.

2.4 Online Positioning

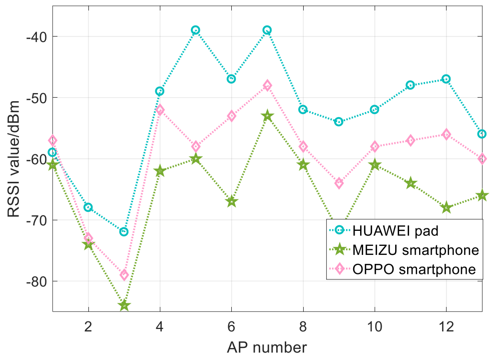
2.4.1 Measurement of Signal Similarity

In the positioning phase, the first step is to calculate the RSS similarity distance and select the K nearest points. Euclidean distance is usually used to determine the degree of matching between the unknown and fingerprint points.

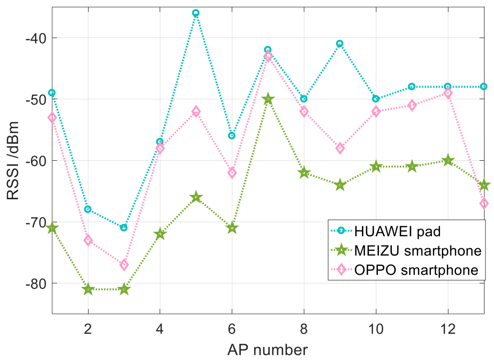
$$d_i = \sqrt{\sum_{j}^{n_1} \left(RSS_j - RSS_{ij}\right)^2}, i = 1,2, \ldots n \quad (2)$$

Where $i = 1,2, \ldots, n$, n1 represents the number of the same APs of i_{th} fingerprint point and an unknown point; RSS_j represents the RSS of j_{th} AP at an unknown point; RSS_{ij} represents the signal strength value of j_{th} AP at i_{th} fingerprint point; and n is the number of fingerprint points stored in the database.

Figure 4 shows high similarity between two signal strength curves. The Euclidean distance is unsuitable for dealing with device heterogeneity. Thus, we use morphology similarity distance to replace the Euclidean distance.



(a)



(b)

Figure 4. Different RSSs received by dissimilar devices: (a) Point a, (b) Point b.

This method requires that the RSS vector of each unknown point should be arranged in the same order as the fingerprint point it will be compared with. The equation of morphological similarity distance calculation is expressed as follows:

$$D_{MSD}(P_i,P_j)=\sqrt{\sum_{m=1}^{n}\left(RSS_{im}-RSS_{jm}\right)^2}\times\left(2-\frac{\left|\sum_{m=1}^{n}\left(RSS_{im}-RSS_{jm}\right)\right|}{\sum_{m=1}^{n}\left|RSS_{im}-RSS_{jm}\right|}\right) \quad (3)$$

where P_i, P_j represents the AP RSSI sequence of two points; and RSS_{im}, RSS_{jm} respectively represent the RSSI of i_{th} and j_{th} AP.

2.4.2 Outlier Detection for Secondary Selection of Neighbor Points

The fluctuation in Wi-Fi signals is inevitable. As shown in Figure 5, some mismatches are obtained when KNN or WKNN is used. To eliminate the influence of this problem, a secondary selection of neighbor points by means of outlier detection is proposed.

First, the k_{th} distance of each neighbor point is calculated after K neighbor points are acquired by morphological similarity distance calculation, and the k-distance neighborhood $N_k(p)$ of each neighbor point is obtained. Second, the reach distance between neighbor points and other adjacent neighbor points is calculated. The k_{th} reach distance from point o to point p is defined as follows:

$$\text{reach}_{-\text{dist}_k}(p,o)=max\{d_k(o),d(p,o)\} \quad (4)$$

where $d_k(o)$ represents the reach distance of point o and other points and $d(p,o)$ is the distance between points p and o.

Third, the local reachability density $lrd_k(p)$ of point p is calculated as follows:

$$\text{lrd}_k(p)=1/\left(\frac{\sum_{o\in N_k} reach-dist_k(p,o)}{|N_k(p)|}\right) \quad (5)$$

Then, the local outlier factor of each neighbor point is obtained by the following equation:

$$L_LOF_k\mid(p)=\frac{\sum_{o\in N_k}\frac{\text{lrd}_k(o)}{\text{lrd}_k(p)}}{|N_k(p)|}=\frac{\sum_{o\in N_k}\text{lrd}_k(o)}{|N_k(p)|}/\text{lrd}_k(p) \quad (6)$$

where $LOF_k(p)$ is the local outlier factor of point p.

Finally, the local outlier of every neighbor point is compared. If the ratio is greater than 1, then the density of p is less than that of its neighborhood, and point p may be an abnormal point. K'neighbor points are obtained using this method.

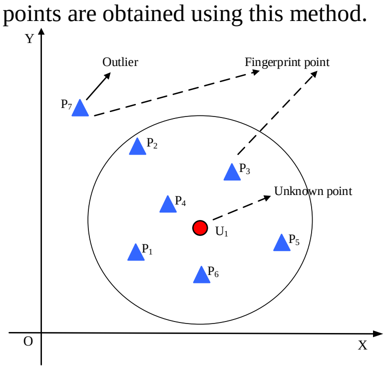


Figure 5. Outlier detection.

2.4.3 Weighting Combination

The law of wireless signal transmission posits that a small RSS similarity distance between neighbor points and the unknown point indicates a close relationship between the geometric positions of the neighbor and the unknown point. Similarly, the center of the neighbor points after outlier detection is theoretically similar to that of the unknown point. Therefore, the distance between neighbor points and their center reflects its contribution to the position of the unknown point to a certain extent. A small distance between the neighbor point and the center of the neighbor points indicates a large contribution of the neighbor point to the position of the unknown point. Thus, we use geometric distance and signal morphology similarity distances to determine the combined weight after the dimensionless treatment.

$$(X_{\text{center}},Y_{\text{center}},Z_{\text{center}})=\frac{1}{k}\sum_{i}^{k}(X_i,Y_i,Z_i) \quad (7)$$

$$l_{ic}=\sqrt{(X_i-X_{\text{center}})^2+(Y_i-Y_{\text{center}})^2+(Z_i-Z_{\text{center}})^2} \quad (8)$$

where $(X_{\text{center}},Y_{\text{center}},Z_{\text{center}})$ are the centers of the neighbor points; (X_i,Y_i,Z_i) are the coordinates of i_{th} neighbor point.

The scaling factors of l_i and d_i are different. Thus, we must map them to a uniform range using Equations (9) and (10). This step also reduces the influence of device heterogeneity to some extent.

$$l'_{ic}=\left|\frac{l_{ic}-\text{Mean}(l_{1c},l_{2c}\dots l_{k'c})}{\text{Std}(l_{1c},l_{2c}\dots l_{k'c})}\right| \quad (9)$$

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$$d_i' = \left|\frac{d_i - \mathrm{Mean}(d_1, d_2 \dots d_{k'})}{\mathrm{Std}(d_1, d_2 \dots d_{k'})}\right| \tag{10}$$

where *Mean* and *Std* represent the mean and variance value functions, respectively.

Given the influence of two kinds of distance on the position of the unknown point, we combine the mapping values of these distances to determine the combined weight. The weight is described as follows:

$$p_i = \frac{\frac{1}{l_{ic}} + \frac{1}{d_i}}{\sum_1^{k'} \frac{1}{l_{ic}} + \sum_1^{k'} \frac{1}{d_i}} \tag{11}$$

where p_i denotes the influence weight of the i_{th} neighbor point on the result of the location, and i =1, 2…*k'*.

The last step is using the weighted mean to obtain the position of the unknown point. The weight is obtained by Equation (12), and the coordinates of the unknown point are acquired using the following equation:

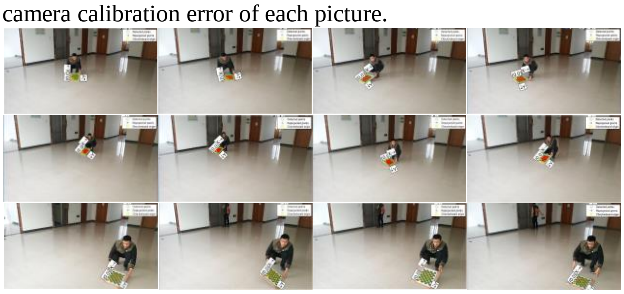
$$(\hat{X}, \hat{Y}, \hat{Z}) = \sum_i^{k'} p_i (X_i, Y_i, Z_i) \tag{12}$$

where$(\hat{X}, \hat{Y}, \hat{Z})$ are the final coordinates of an unknown point.

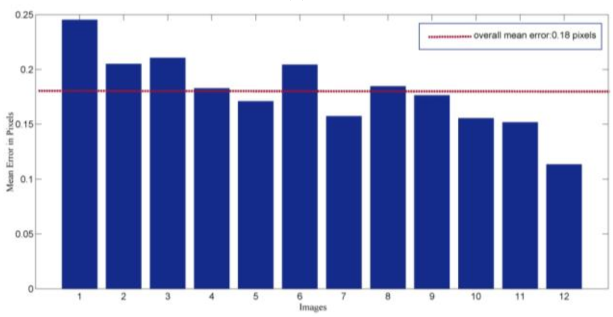
3. EXPERIMENTS AND ANALYSIS

3.1 Trajectory Tracking of Ordinary Users via Video Surveillance Cameras

We select 12 pictures for camera calibration. Figure 6 shows the camera calibration error of each picture.



(a)



(b)

Figure 6. Camera calibration: (a) Pictures for camera calibration, (b) Camera calibration error of each picture.

Given that two routes are chosen for collection, two intrinsic camera parameter matrixes, two extrinsic camera parameter matrixes, and two translation vectors will be obtained. Rotation matrixes are easily obtained as follows:

$$\begin{bmatrix} 3672.772 & -906.635 & 6.556 & 30878841 \\ 620.375 & -64.17 & 3093.362 & 6360397 \\ 0.319 & -0.899 & 0.301 & 2713.113 \end{bmatrix},$$

$$\begin{bmatrix} 2474.458 & -2576.91 & 986.863 & 6434200 \\ -595.223 & -480.03 & 2955.391 & 6464158 \\ -0.240 & -0.941 & 0.238 & 2403.941 \end{bmatrix}$$

Users' relative trajectories can be obtained rapidly using the parameters and rotation matrixes we calculated above and the results we acquired in the process of moving target detection. Figure 7 shows the relative path.

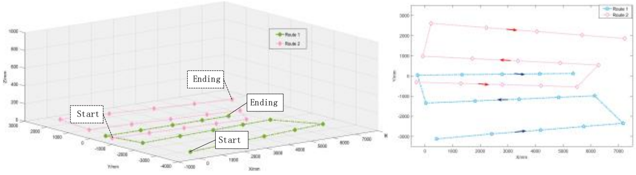


Figure 7. Relative acquisition line of the collector.

Then, the relative path is translated into the coordinate system we defined for positioning. Figure 8 shows the absolute path.

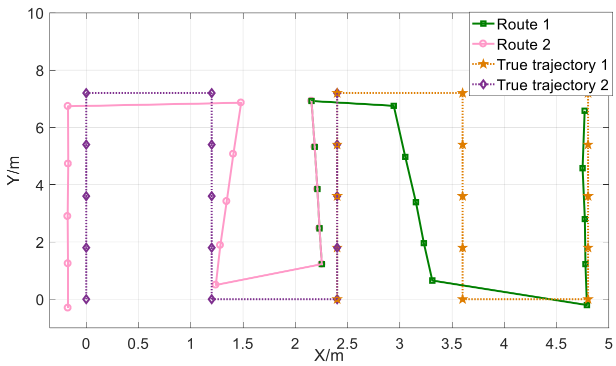


Figure 8. True trajectory and the calculated path.

The true coordinate of fingerprint points and the calculated coordinates are compared by monocular vision method based on plane constraints. As shown in Figure 9, the error of coordinates of most sampling points is less than 0.8 m. Thus, the method can be used to rapidly collect information for fingerprint database building and updating.

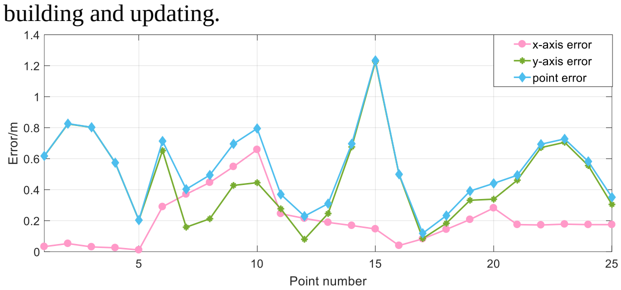


Figure 9. Error of the calculated coordinates by monocular vision method based on plane constraints.

3.2 Localization Experiments

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A method was proposed to construct and update the fingerprint database via implicit crowdsourcing, and some algorithms were used in online positioning to eliminate the influence of device heterogeneity and neighbor mismatching. We designed several experiments to illustrate the effectiveness of the proposed methods.

We used KNN, WKNN, and improved WKNN algorithms to show the positioning effect. Among the algorithms, improved WKNN was divided into two different algorithms, namely, IWKNN1 and IWKNN2. IWKNN1 comprised the process of signal similarity calculation by morphological similarity distance, outlier detection, and combination weighting. IWKNN2 had the same process as IWKNN1, but the Euclidean distance replaced the morphological similarity distance.

The first experiment was performed to demonstrate the improved effect of the proposed method on dealing with the problem of device heterogeneity. We used the HUAWEI pad to collect the information of fingerprint points and used OPPO and MEIZU smartphones to collect the information of unknown points. We selected 150 unknown points. Table 1 and Table 2 respectively show the results of four algorithms when using OPPO and MEIZU smartphones for positioning. Notably, IWKNN1 has a better effect and lower point mean, max, and min errors than other algorithms.

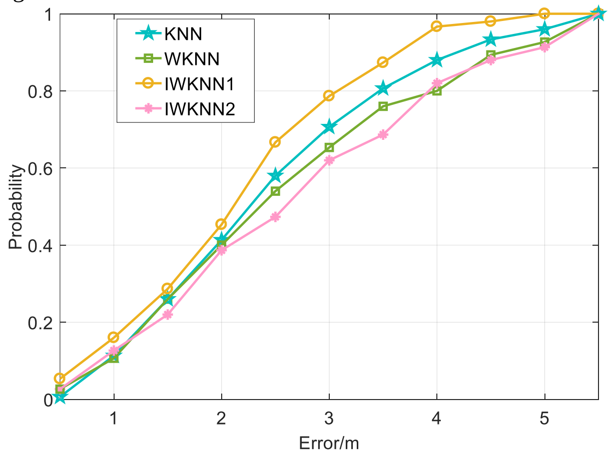
Eigenvalues	KNN	WKNN	IWKNN1	IWKNN2
Mean error(m)	2.452	2.613	2.134	2.751
Max error(m)	5.839	6.442	4.878	7.836
Min error(m)	0.433	0.205	0.052	0.069

Table 1. Positioning results when using OPPO smartphone.

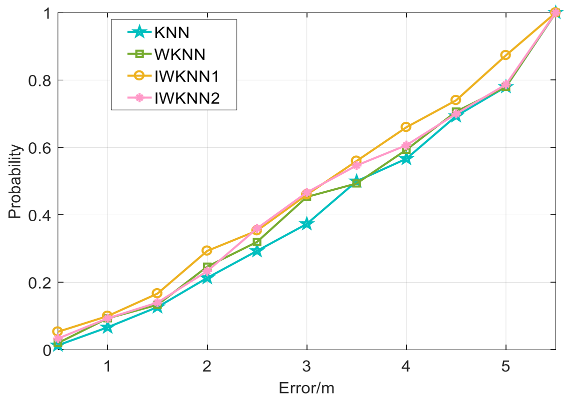
Eigenvalues	KNN	WKNN	IWKNN1	IWKNN2
Mean error(m)	3.535	3.449	3.243	3.405
Max error(m)	7.031	7.092	7.970	7.299
Min error(m)	0.379	0.432	0.100	0.226

Table 2. Positioning results when using MEIZU smartphone.

The CDF plots of error for the compared algorithms are shown in (b). Figure 10. Notably, IWKNN1 has higher accuracy than other algorithms.



(a)



(b)

Figure 10. CDF plots of error for the compared algorithms: (a) Positioning results when using OPPO smartphone; (b) Positioning results when using MEIZU smartphone.

The second experiment was conducted to verify the practicality of the proposed method for building and updating a fingerprint database via implicit crowdsourcing. Similarly, we conducted an experiment on two groups: one used the true coordinates of these fingerprint points, and the other used the calculated coordinates by video sequence. Table 3 and Table 4 respectively show the results of the two groups. Although some errors exist for each fingerprint point, the proposed method still keeps the same accuracy as the traditional method for collecting the information individually. Furthermore, the proposed method costs less time and human resources.

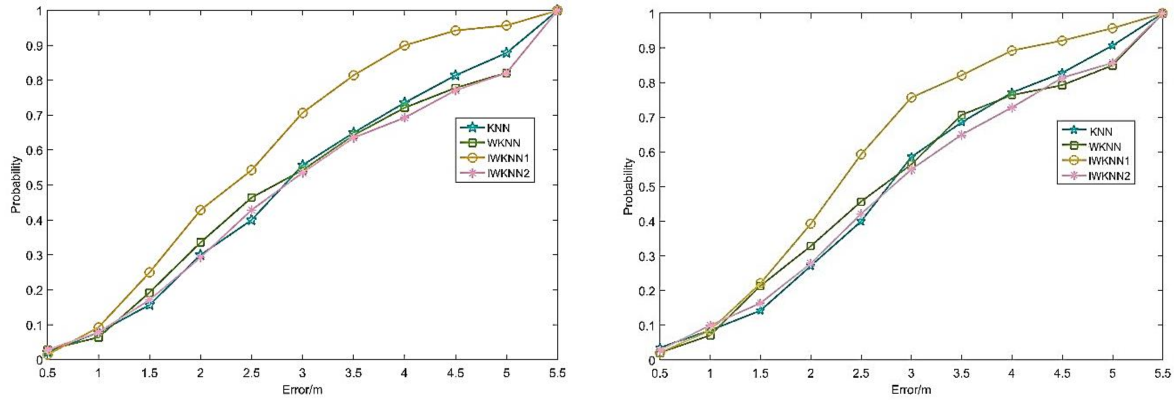
Eigenvalues	KNN	WKNN	IWKNN1	IWKNN2
Mean error(m)	2.960	2.958	2.427	3.054
Max error(m)	6.529	6.680	6.925	7.693
Min error(m)	0.240	0.230	0.315	0.018

Table 3. Positioning results when using the true coordinates of fingerprint points.

Eigenvalues	KNN	WKNN	IWKNN1	IWKNN2
Mean error(m)	3.027	3.067	2.457	3.178
Max error(m)	6.762	6.896	6.548	7.656
Min error(m)	0.436	0.114	0.281	0.116

Table 4. Positioning results when using the calculated coordinates of fingerprint points.

The CDF plots of error for two groups are shown in Figure 11. Notably, the proposed method for fingerprint database has sufficient practicality.



(a) (b)

Figure 11. CDF plots of error for two groups: (a) Positioning results when using the true coordinates of fingerprint points; (b) Positioning results when using the calculated coordinates of fingerprint points.

4. CONCLUSION AND FUTURE WORK

In this study, we have presented a rapid method to construct a Wi-Fi fingerprint database. This method improves the efficiency of fingerprint collection and the possibility of the collection by crowdsourcing. The improved WKNN can deal with the problems of device heterogeneity, signal fluctuation, and neighbour mismatching with high accuracy.

In our future work, we will solve the problem of camera distortion and demonstrate the availability of the proposed method in a large area. When deployed in real and complicated indoor environments, the accuracy and stability of the system will be improved. Other technologies, such as PDR and geomagnetism-aided positioning, will also be integrated into the current system to improve the localization accuracy.

ACKNOWLEDGEMENTS

This work is supported by the Fundamental Research Funds for the Central Universities (2021ZDPY0220), Excellent Youth Foundation of Hubei Scientific Committee (2021CFA040), Guangdong Basic and Applied Basic Research Foundation (2021A1515110343) and Hubei Province International Science and Technology Collaboration Program (2021EHB012).

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