

Research Article

Indoor Mobile Localization Based on Wi-Fi Fingerprint's Important Access Point

Pei Jiang,¹ Yunzhou Zhang,² Wenyan Fu,² Huiyu Liu,² and Xiaolin Su²

¹*Department of Weaponry Engineering, Naval University of Engineering, Wuhan 430033, China*

²*College of Information Science and Engineering, Northeastern University, Shenyang 110819, China*

Correspondence should be addressed to Yunzhou Zhang; zhangyunzhou@ise.neu.edu.cn

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With the development of the wireless communication technology and intelligent mobile phone, the positioning services based on Wi-Fi and mobile phone are increasingly demanded. In this paper, a Wi-Fi fingerprint localization method is proposed on the basis of important access points (IAP). For the Wi-Fi fingerprint, Wi-Fi access point with the highest received signal strength (RSS) is denoted as the important access point. At the localization stage, the fingerprints are chosen with the same IAP as the estimated fingerprint from the database. Then, the distance and the AP repetition of the fingerprints are used to calculate the similarity degree. The location of the fingerprint which matches the estimated fingerprint well can be regarded as the estimated location. Experimental results show that the proposed algorithm can achieve high accuracy in indoor environment.

1. Introduction

With the rapid development of mobile communication and the pervasive computing technology, the requirement of obtaining location-aware service is rapidly increasing. Though Global Positioning System (GPS) can provide accurate and reliable position information for location services, it cannot be used effectively under indoor environment [1]. To overcome this limitation, researchers have proposed many creative localization technologies such as sensor network, RFID, and Wi-Fi [2, 3]. Among them, Wi-Fi positioning technology has attracted extensive attention because it is built upon mobile phones, which are used widely all over the world [4]. The crowded places, such as street, office buildings, shopping malls, hotels, and airports, usually have a lot of AP hot spots, which form a wide coverage of Wi-Fi network [5]. Therefore, it is feasible and practicable to adopt the Wi-Fi network and mobile phone to implement personnel positioning under indoor environments.

Wi-Fi-based indoor positioning can be divided into two categories according to the working basis. One consists of the localization algorithms based on signal propagation

model [6–8]. The other includes those algorithms based on position fingerprint [9–11]. The former uses the signal propagation model to convert measured signal strength into distance information. Then, the target coordinates can be calculated according to the distance between the moving target and the multiple access points with known coordinates. To accomplish that, it is necessary to perform coordinate planning on the areas to be localized and accurately obtain the coordinates of Wi-Fi access point. For ordinary multistory building, the actual deployment of Wi-Fi access points is irregular, since it is seriously influenced by some factors such as the building structure. Thus, it is very complex to fulfill the establishment and calculation of the AP coordinates. At the same time, in the procedure of signal transmission, Wi-Fi signal is vulnerable to environmental factors such as walls, doors, and windows, even the movement of people. Besides, the degree of attenuation is closely related to the obstacles' shape, size, and material. Therefore, in the indoor environment with complex structure, the signal propagation model cannot accurately describe the relationship between actual distance and the signal strength.

The algorithm of fingerprint localization mainly consists of two parts, including offline establishment of location-fingerprint database and online positioning. At the stage of database establishment, some appointed locations in the building are sampled. A collection of Wi-Fi signals and their intensity will be recorded and considered as position fingerprint. At the stage of online positioning, fingerprint information is collected around the position to be localized. Compared with fingerprints in offline database by matching strategy, the position whose fingerprint can attain the best match is chosen as the final estimated position. In contrast, although the Wi-Fi fingerprint-based positioning technology needs to make fingerprint database at the early stage, it can effectively avoid the influence of building structure. Furthermore, fingerprint-based methods do not require that Wi-Fi access points are known beforehand. Therefore, it has a higher practicability.

This paper proposes a Wi-Fi fingerprint-based positioning algorithm with important access points to estimate the position of mobile phone by analyzing the experimental test of indoor Wi-Fi signal. The proposed algorithm does not require the environment layout and additional equipment. Compared with classic fingerprint localization algorithm, it effectively reduces the computation load and can obtain high localization accuracy.

The main contributions of this paper are as follows.

- (1) We proposed to establish an offline database using simplified information. Only the AP information of each fingerprint is reserved. Thus, we can avoid the disadvantages of traditional methods that the fingerprint database needs to sample all the APs.
- (2) A fingerprint matching algorithm is put forward based on important AP, which effectively narrows down the scope of the database retrieval. Therefore, it can reduce the computation and eliminate the interference factors to obtain a higher positioning accuracy.
- (3) We proposed a fingerprint matching algorithm by considering the fingerprint distance and the matching rate of APs. The corresponding fingerprint in the database is extracted accurately so that the accuracy of mobile positioning is improved.
- (4) We do not need to reconfigure or set up the indoor environment. A more accurate moving target positioning can be achieved in multistory buildings with a mobile phone.

The remainder of this paper is organized as follows. Section 2 presents the experimental analysis of Wi-Fi signals, which is the basis for the algorithm in this paper. Section 3 depicts the Wi-Fi position fingerprint localization algorithm based on the important access point in detail. Section 4 shows the experiment to verify the validity of the proposed algorithm. Section 5 draws the conclusion.

2. Related Work

Localization is a vital information service for mobile phone. For outdoor situation, GPS positioning can be used accurately and stably. Right now, two methods, including model-based localization and fingerprint-based location, are typically used in indoor situation.

Model-based localization achieves estimated target position by establishing mathematical models, which refer to the combination of collected physical data and distance or position. A frequently used technology is log-distance path loss (LDPL). It estimates RF signal propagation distance according to the strength of the received signal. The work in [12] deploys a Wi-Fi network detector at a known position. By analyzing the received signal strength (RSS) from different APs, a map is drawn based on LDPL model. The work in [13] uses Bayesian hierarchical model to reduce the number of training positions. The computational complexity of localization procedure is reduced effectively. However, these algorithms need to model the coordinates of the building, and all the APs' coordinates must be known. The procedure is too complicated to be put into practice.

In most indoor localization, which is for the purpose of practical application, fingerprint-based localization is frequently used. With different wireless network information collected in the building as its position label, fingerprint profiles can be mapped with the wireless network signal intensity. In the localization procedure, by collecting wireless signals around an unknown position and matching them with the established fingerprint map, we can estimate the position of moving targets. Most of the fingerprint-based localization techniques, such as RADAR system [14], use radio signals. Based on RADAR system, Horus [15] uses RSS positional relationship of a random guess strategy and maximum likelihood algorithm to estimate the target's position. For fingerprint classification, OIL [16] uses the Thiessen polygons planning which can improve the accuracy of moving target localization. The work in [17] presents a local localization estimation method. It localizes moving target via the utilization of various characteristic parameters (such as sound, light, color, and Wi-Fi) around the structure.

All the algorithms above need to survey the building layout. Besides, the scale of fingerprint database is too large; the location matching process is computationally intensive and time-consuming. Therefore, they lack practicality and flexibility. In [18], a hierarchical clustering method is used to partition the RSS space for Wi-Fi-based indoor localization. To choose the best transmitters in a partition, the amount of RSS variance, which is attributable to different base stations or access points, is evaluated by transforming the RSS tuples into principal components. In [19], the information about the location is ranked in a hierarchical way by identifying the building, the floor, the room, and the geometric position. The fingerprint localization method adopts a previously stored map of the signal strength at several positions and determines the position by similarity functions and majority rules.

On the basis of the above research, we proposed a new algorithm for indoor localization with Wi-Fi signal.

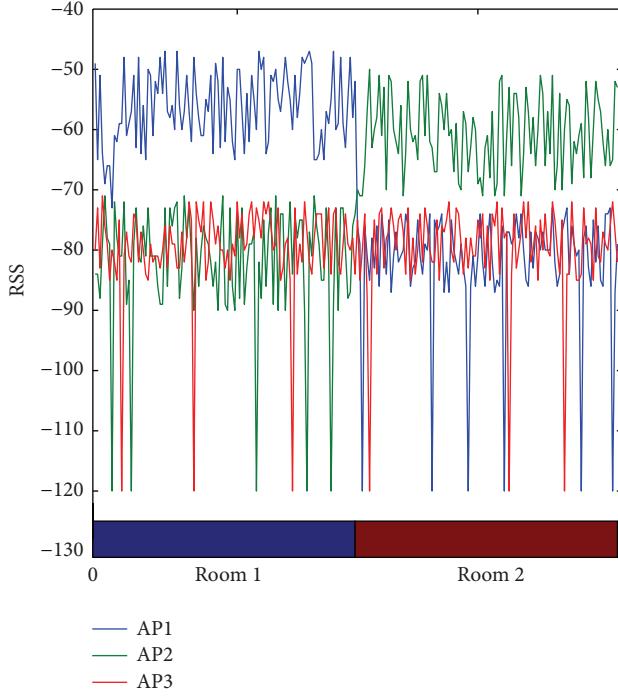


FIGURE 1: Contrast of RSSI in adjacent classrooms.

3. Wi-Fi Signal Analysis

According to the propagation model of Wi-Fi signal, the signal intensity will decline with the propagation distance increasing. Due to the influence of the building structure, the signal intensity will undergo a sharp decay when passing through walls. Therefore, Wi-Fi signals spreading to different rooms from the same AP may have different attenuation and different ranges of their RSS value. Aiming at this problem, we have carried out some field tests and experimental analysis.

3.1. Contrast of Wi-Fi Signals from Adjacent Rooms. Through experiments, it can be found that several APs' signal can be detected in indoor environment covered by Wi-Fi. For the two adjacent classrooms, we conducted sampling at random position for 109 times in each classroom. Detected APs and their corresponding RSS value are recorded. In this procedure, RSS values of 3 common APs detected in both classrooms were compared. Due to the signal fluctuation, there was occasionally some loss of AP signal at certain sampling time. For this situation, the corresponding RSS was set to default value as -120 db. The contrast of Wi-Fi signal strength in different rooms is shown in Figure 1.

As can be seen through the field experiment, AP1 was placed close to Room 1, but far from Room 2. AP2 is just the opposite. AP3 is a wireless network provided by a cell-communication provider with wide coverage. Figure 1 shows that, for AP1 and AP2, the RSS values detected from two adjacent classrooms have significant difference. But for AP3, there is little difference. At the same time, APs with biggest signal strength detected in each room are different. Generally, it is not AP3.

According to the experiment above, a Wi-Fi network with small scale is more vulnerable to the building structure. Those APs deployed indoors have different signal intensity values in different rooms. However, the signal of widely covered Wi-Fi network from AP provider is less affected by building structure.

3.2. Wi-Fi Signal Sampling and Processing. Since the signal is vulnerable to the environment interference, RSS value is always in the state of fluctuation. In order to gain more reasonable Wi-Fi information via fingerprint sampling, we continuously collect data at the sample points and filter the data.

If the sample time is T_s and the sample rate is f , the number of the collected data groups will be

$$N_{Ts} = T_s \cdot f. \quad (1)$$

In the procedure of sampling, there will be some interferential APs influencing the establishment of a fingerprint. For example, a temporary AP or some others far from current location can only be detected occasionally. Thus, we filter the APs before filtering RSS data. During the sampling, we consider an AP with lower detected number of time $N_{Ts}(\text{ap})$ than the threshold N_{th} as an interference AP and then abandon them. That is,

$$N_{Ts}(\text{ap}) \begin{cases} \leq N_{\text{th}} & \text{abandoned} \\ > N_{\text{th}} & \text{preserved.} \end{cases} \quad (2)$$

Among the sampling data, each preserved AP has $N_{Ts}(\text{ap})$ fluctuating RSS values. Assume $\text{Rssi}(n)$ as the n th detected RSS value of a specified AP.

Due to the influence of environmental factors, different RSS value is always seen at different sampling time for the same AP at the same location. As shown in Figure 1, RSS value of Wi-Fi signal fluctuates frequently. Sometimes, the measured value is far away from the true values. To filter out the outliers and make the measurement more useful, we adopt the iterative recursive weighted average filter [20] to process the obtained RSSI data. It has high smoothness and needs small computation and storage, which is suitable for running on embedded systems such as a mobile phone.

The procedure of iterative recursive weighted average filtering algorithm is as follows.

Step 1. Initialization: $F1(1) = \text{Rssi}(1)$, $F2(1) = \text{Rssi}(1)$, and $F3(1) = \text{Rssi}(1)$.

Step 2. If $n = 2$, then

$$\begin{aligned} F1(n) &= \beta_1 \text{Rssi}(n-1) + \beta_2 \text{Rssi}(n), \\ F2(n) &= \beta_1 F1(n-1) + \beta_2 F1(n), \\ F3(n) &= \beta_1 F2(n-1) + \beta_2 F2(n). \end{aligned} \quad (3)$$

When $n > 2$, go to Step 3.

Step 3. Consider

$$\begin{aligned} F1(n) &= \beta_3 \widehat{\text{Rssi}}(n-2) + \beta_4 \widehat{\text{Rssi}}(n-1) + \beta_5 \text{Rssi}(n), \\ F2(n) &= \beta_3 F1(n-2) + \beta_4 F1(n-1) + \beta_5 F1(n), \\ F3(n) &= \beta_3 F2(n-2) + \beta_4 F2(n-1) + \beta_5 F2(n). \end{aligned} \quad (4)$$

Step 4. Consider

$$\widehat{\text{Rssi}}(n) = F3(n). \quad (5)$$

Here, $[\beta_1, \beta_2]$ and $[\beta_3, \beta_4, \beta_5]$ are weighted factors which satisfy the following conditions:

$$\begin{aligned} \beta_1 + \beta_2 &= 1, \\ \beta_3 + \beta_4 + \beta_5 &= 1. \end{aligned} \quad (6)$$

By adjusting the value of these weighted factors, we can get different filtering effects. In this paper, we choose $[\beta_1, \beta_2] = [0.8, 0.2]$ and $[\beta_3, \beta_4, \beta_5] = [0.8, 0.15, 0.05]$.

4. Fingerprint Localization Based on Important Access Point

In this paper, we put forward an idea named “Wi-Fi fingerprint-based localization based on the important access points.” Among the fingerprint data collection, the APs’ RSS values are collected and sorted in descending order. One or several top ranked APs are considered as important access points (IAP) of Wi-Fi fingerprint. In the procedure of fingerprint matching positioning, in order to reduce computation and positioning time, some fingerprints are screened when they are the same as the fingerprint IAP in the fingerprint database. We need to consider the distance between the fingerprints and the contact ratio of APs in the fingerprint. Then, the location of the fingerprint with highest matching degree is chosen as the final estimated location.

Wi-Fi fingerprint refers to the feature data characterizing the location information of a specific location, where the collected Wi-Fi signal is unique. According to the comparative experiment results of Section 2 in different rooms, Wi-Fi signal strength collected in a specific room can be used as this room’s Wi-Fi fingerprint.

The important access point is one or several Wi-Fi access points which have the strongest signal strength. The obtained Wi-Fi fingerprints which comprise a plurality of signal strength information of the Wi-Fi APs are considered as the important features of the fingerprint.

In indoor environments, various Wi-Fi access points are dispersed and usually arranged in different rooms. The detected signal intensity is seriously influenced by the number of walls where Wi-Fi signal passes through. Therefore, signal strengths detected in different rooms from the same Wi-Fi AP are different. Simultaneously, Wi-Fi APs with the strongest signal strength detected from different rooms at the same time are deferent.

In view of the above points, this paper proposes a Wi-Fi fingerprint-based localization algorithm based on the IAP location. The unknown fingerprint is generated after acquiring the AP’s signal strength around the unknown location. Those APs which have the strongest signal strength are selected as IAP. The reference fingerprints which are the same as the unknown fingerprint’s IAP are extracted from the fingerprint database. Then, we calculate the similarity between the reference fingerprint and the unknown fingerprint.

The room, which the reference fingerprint with the highest similarity is in, is selected as the estimated room of the unknown fingerprint. The algorithm is divided into two stages: the establishment of the offline Wi-Fi location-fingerprint database and online positioning. The structure of the algorithm is shown in Figure 2.

4.1. Establishment of Wi-Fi Fingerprint Database. In this paper, the research target is to locate which room the telephone is in. Therefore, we should sample and record the information of wireless signals in different rooms of the building. To describe the strength characteristic of the Wi-Fi signal in a better way, it is necessary to set up sampling points at different locations in the room. And each point should be sampled by multiple times. Furthermore, we should process the sampled data with the filtering algorithm mentioned in Section 3.2. For each position’s fingerprint, we sort the Wi-Fi access points according to the signal strength. Then, we can obtain important information of every fingerprint’s access point.

4.2. Online Positioning Based on Fused Matching. At the stage of online positioning, users hold the mobile phone to detect the signal strength around AP and collect the location fingerprint. Then, the IAP of fingerprint can be marked. We can search for the fingerprint which has consistent access point with the fingerprint to be located in the database. The matching operation between the search results and target fingerprints is implemented to estimate the position of the target fingerprint. Currently, commonly used fingerprint matching algorithms include NN (Nearest Neighbor) [14], KNN [11], WKNN (Weighted KNN), and Bayesian probabilistic algorithm [13]. Manhattan and Euclidean distances are frequently used to compare vector distance.

For the KNN, WKNN, and Bayesian probabilistic algorithm, one needs to know the fingerprint coordinate information in the database established beforehand. Since we do not need this coordinate calculation, the NN algorithm is adopted. First of all, we screen out the fingerprint which has the same IAP as the unknown fingerprint in the database. Then, we calculate the similarity between the unknown fingerprint and results which are checked out from the fingerprint database. Finally, we find out the fingerprint which has highest similarity with the unknown fingerprint. Then, the corresponding room will be considered as the estimated result.

In the procedure of matching and positioning, the APs detected by unknown fingerprint are likely to be inconsistent with those of the matching fingerprint in the database.

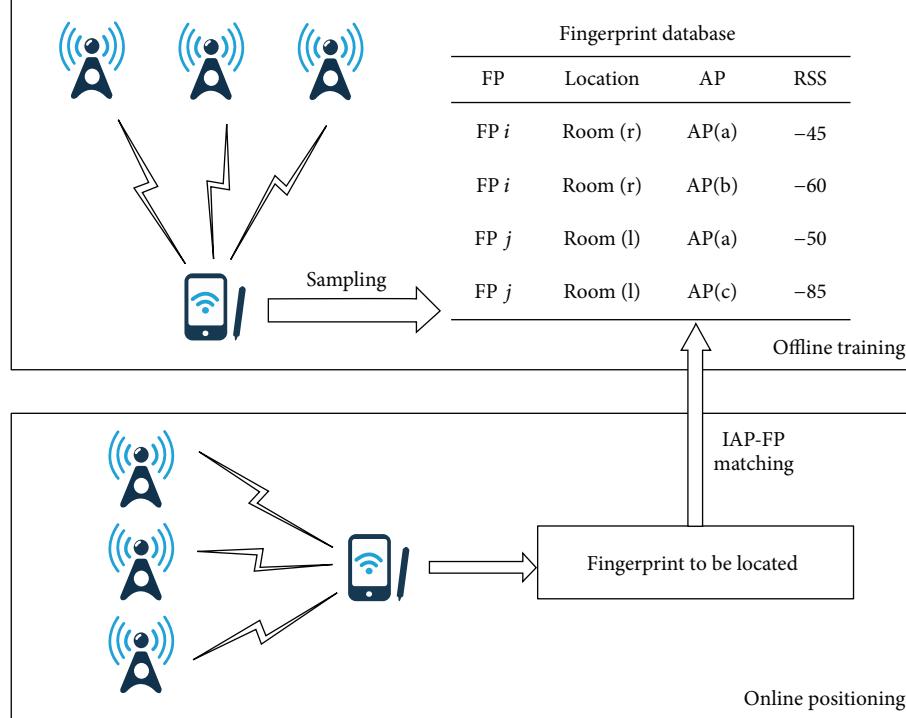


FIGURE 2: IAP-FP algorithm.

Even if the two fingerprints have the same IAP, a big difference between the two portfolios may still mean that they are not in the same room. Therefore, we have to consider the matching degree of the AP portfolio when calculating the fingerprint matching similarity. For the same matching distance based on the classical NN algorithm, the repetition rate of two matched fingerprint APs is low. Therefore, new matching distance is defined as the result of the distance minus the corresponding weights.

In this paper, we define the distance between unknown fingerprints f_0 and f_i , the fingerprints in database, as

$$D(f_0, f_i) = \left| \sum_{j=1}^n (f_0(j) - f_i(j))^q \right|^{1/q}, \quad (7)$$

where j is the j th unknown fingerprint AP, $f_0(j)$ represents unknown fingerprint of the j th AP's RSSI value, and $f_i(j)$ represents RSSI value of AP _{j} in fingerprint f_i . If the AP _{j} is not detected in f_i , it will be set as -120 dB. It is on behalf of the Manhattan distance when $q = 1$ and the Euclidean distance when $q = 2$. q 's value is selected in the actual positioning according to its requirement and positioning accuracy. Experiment result shows that the positioning accuracy of the NN algorithm does not become better with q 's value increasing. When $q = 2$, the positioning performance is better. Therefore we choose $q = 2$.

The similarity degree between unknown fingerprint and fingerprint database plays a decisive role in the final estimation. In this paper, similarity calculation considers

the NN distance and AP repetition rate. The formula is as follows:

$$\begin{aligned} S(f_0, f_i) &= \frac{1}{D(f_0, f_i)(1 - \alpha \cdot Ne_i/Nd_i)} \\ &= \frac{Nd_i}{D(f_0, f_i)(Nd_i - \alpha \cdot Ne_i)}, \end{aligned} \quad (8)$$

where Nd_i is the detected number of APs from the unknown fingerprint f_0 and Ne_i is the number of same APs detected in two fingerprints. α is a proportional factor, which can control the influence of APs' repetition rate. If α is 0, it means that the repetition rate of AP is not considered. If α becomes larger, it means that there is closer relation between similarity and the repetition rate of AP. In this paper, α is set according to real experiment. The room in which the fingerprint has the highest similarity between fingerprint database and the unknown fingerprint is selected as the final room.

5. Experiment Result and Analysis

In order to verify the validity of the algorithm proposed in this paper, experiments are carried out in a teaching building which has normal classrooms. Many APs are distributed in the teaching building, but their positions are unknown. In the meantime, not every classroom has an AP. Nevertheless, every classroom can pick up several AP signals. An Android application is developed for Wi-Fi sampling and works on a mobile phone to collect data. The structure of teaching building is shown in Figure 3. For the 20 classrooms at Floors 1st, 2nd, and 3rd, 8~14 sampling points are randomly selected

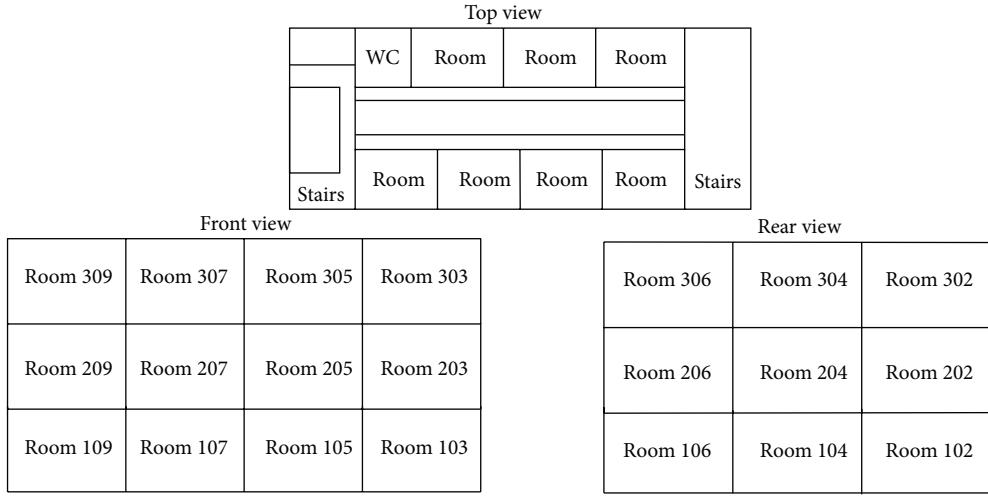


FIGURE 3: Layout of the building.



FIGURE 4: Position fingerprint sampling.

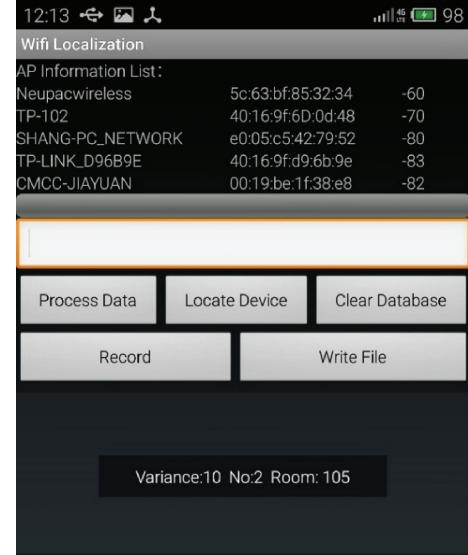


FIGURE 5: Fingerprint positioning result.

in each room to establish the fingerprint database. Totally, 220 fingerprints are sampled and recorded.

Figure 4 shows the interface of our Android application when collecting data. The upper part of the interface shows the detected ID and the strength of Wi-Fi signals. White text-box is used to input the position information of sampled fingerprint, such as room number. With the Record operation, the system can automatically record the Wi-Fi signal data and filter it to get a position fingerprint. These data will be stored orderly in the mobile phone's memory. At the positioning stage, no data is needed to be typed in the text-box.

Figure 5 shows the situation when positioning result is acquired. Variance and room number are displayed on the screen of mobile phone.

In order to verify whether the proposed IAP-Fingerprint (IAP-FP) algorithm can effectively reduce the computation load of fingerprint matching, we analyze the allocation proportion of IAP in fingerprint database. We count the number of fingerprints which consider AP_i as IAP and calculate its proportion in the whole database. The result is shown in

Figure 6. From the result we can find that, no matter which one of the twelve APs is considered as IAP by the unknown fingerprint, it only needs at most 23%, the highest detective portion with AP_3 , of the whole fingerprint database for matching. Since matching range is effectively cut down, the computation load of fingerprint matching is reduced greatly.

In order to verify whether the reduction of matching range will decrease the accuracy of fingerprint matching, we conducted positioning experiment for 220 times. In every experiment, a fingerprint is extracted from the fingerprint database. Then, it is removed from the database. This fingerprint is regarded as the one to be located and matched with other fingerprints in the database. To verify the performance of our proposed algorithm, we compare it with three other Wi-Fi-based fingerprint localization algorithms. The first one

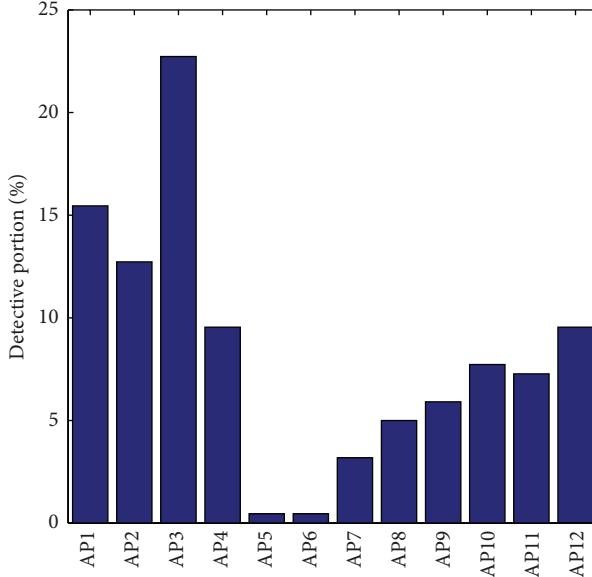


FIGURE 6: Distribution of IAP-Fingerprints in database.

TABLE 1: Localization accuracy with different parameters.

Algorithms	Parameters	Accurate samples	Percentage
NN	None	151	68.6%
Reference [18]	None	159	72.3%
Reference [19]	None	163	74.1%
IAP-FP	$M_f = 1$	178	80.9%
IAP-FP	$M_f = 2$	189	85.9%
IAP-FP	$M_f = 3$	165	75.0%

is classical NN algorithm, while the other algorithms come from literature [18] and [19], respectively. The statistical result of positioning is shown in Table 1.

The result shows that the accuracy of our IAP-FP algorithm is significantly higher than the classic NN fingerprint location algorithm and the methods in [18, 19]. The main reason is that the IAP-FP algorithm effectively reduces the scope of fingerprint matching. This process not only reduces the amount of computation, but also discards some fingerprints which have high similarity but not in the same classroom with the fingerprint to be positioned.

In this experiment, we set three IAP-FP parameters to analyze the algorithm's performance. When $M_f = 1$, the fingerprint, whose 1st IAP in the database is the same as 1st IAP of unknown fingerprint, is selected for matching and positioning. When $M_f = 2$, the fingerprint, whose 2nd IAP in the database is the same as 2nd IAP of unknown fingerprint, is selected for matching and positioning. When $M_f = 3$, the same procedure is repeated with the fingerprint whose 3rd IAP in the database is the same as 3rd IAP of unknown fingerprint. As M_f increases, matching range and computation load are gradually reduced. As it can be seen from the statistics, when $M_f = 2$, the algorithm obtains the highest accuracy. When $M_f = 1$, the search range is still large and

TABLE 2: Faults analysis of IAP-FP with $M_f = 2$.

Sample no.	3	4	5	32	57	60	65	72
Correct	R103	R103	R103	R109	R207	R205	R205	R205
Estimated	R203	R203	R203	R209	R308	R203	R203	R203
Sample no.	74	85	87	95	97	98	103	141
Correct	R203	R303	R303	R305	R305	R305	R307	R306
Estimated	R205	R203	R202	R303	R306	R307	R207	R205

the positioning result is affected by interferential fingerprints, which inevitably leads to some deviations. When $M_f = 3$, the search range is too small. In some cases, it might be 0 and cannot be matched. Therefore, the positioning accuracy will be decreased. When $M_f = 2$, the search range is reasonable and the localization accuracy is highest.

Table 2 shows the faults analysis of the proposed IAP-FP algorithm. Referring to the building map, we can find that 12 faults, which are recorded in Blue, out of 16 give the room neighbour adjacent to the correct one. For instance, the estimated room of Sample 3 is R203, which is adjacent to the correct result, R103. In other words, although the estimation of these 12 faults is not correct, they are close to correct answer. At the same time, 4 faults, which are recorded in Purple, out of 16 are wrong. For instance, the estimated room of Sample 57 is R308, while the correct room should be R207.

6. Conclusion

For indoor environment covered by Wi-Fi signal, we propose a Wi-Fi fingerprint-based localization algorithm based on the important access point. With the proposed algorithm, we can accurately estimate the room which the mobile phone is in. With the fingerprint distance and Wi-Fi AP's matching, the algorithm can effectively reduce the range of fingerprint matching. Finally, it can give an accurate estimation without the knowledge of building structure and the information of APs' distribution. Therefore, it has high practical value for indoor personal localization.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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