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Article

Research on Indoor Passive Positioning Technology Based on WiFi

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Abstract: In recent years, WiFi indoor positioning technology has become a hot research topic at home and abroad. However, at present, indoor positioning technology still has many problems in terms of practicability and stability, which seriously affects the accuracy of indoor positioning and increases the complexity of the calculation process. Aiming at the instability of RSS and the more complicated data processing, this paper proposes a low-frequency filtering method based on fast data convergence. Low-frequency filtering uses MATLAB for data fitting to filter out low-frequency data; data convergence combines the mean and multi-data parallel analysis process to achieve a good balance between data volume and system performance. At the same time, this paper combines the position fingerprint and the relative position method in the algorithm, which reduces the error on the algorithm system. The test results show that the strategy can meet the requirements of indoor passive positioning and avoid a large amount of data collection and processing, and the average positioning error is below 0.5 meters.

Keywords: Indoor positioning; WiFi; location fingerprint; relative position; low frequency filtering

1 Introduction

Nowadays, with the popularity of mobile terminals such as wireless communication tools and smart phones, there is an increasing demand for location information. At present, GPS positioning technology has matured and has achieved wide application in outdoor positioning. However, due to wall interference and other natural factors, GPS cannot meet indoor positioning requirements, so people began to turn into indoor positioning research. Considering the development of wireless network technology, the widespread popularity of WALN, lower positioning cost, and large market space based on Location Based Services (LBS) [1], WiFi-based indoor positioning technology has become a hot topic of current research.

There are various methods for indoor positioning, including wireless network technology, Bluetooth, geomagnetism, ultra-wideband (UWB), infrared, RFID, TOA technology, and probability-based distribution technology [2–4]. Although it is possible to use an image recognition-based technology to observe the position of the person, such a system needs to locate a certain mark or object, and monitoring with a camera device is costly [5]. The positioning mechanism based on TOA (Time of Arrival) [6] means that when the signal propagation speed is a fixed value, the distance is equal to the measurement value of the signal propagation time, but for indoor positioning, the node equipment cost is very limited, space restrictions are strict and there are strict limits on energy consumption. Therefore, TOA technology has a problem of poor practicality in the use of indoor positioning, which results in limited application of TOA technology in indoor positioning. Literature [7–8] describes a probabilistic-based localization algorithm that acquires joint probability distributions from RSS samples and Bayesian criteria to estimate target locations. This introduction mainly discusses indoor positioning technology based on wireless networks [9–10], which can be roughly divided into the following two ways.

Relative position-based calculation method [11]. The method calculates the distance between the reference point and the target to be tested according to the input RSS value or signal power by establishing the relationship between the RSS value or the signal power and the distance, and calculates the position of the target to be tested according to the distance. The method mainly includes two aspects of error: first, the volatility of the RSS value or signal power affects the accuracy of the distance obtained from the relational model; second, there is an error in the algorithm system when estimating the target position based on the distance. In this paper, the low-frequency filtering method is proposed for the first error, which effectively reduces the instability of RSS or signal power. At the same time, the data fast convergence strategy avoids huge data processing and achieves high efficiency and simplicity. For the second type of error, the literature[12] uses a triangle positioning algorithm to estimate the target position by using the distance information of the object to be tested to at least three known reference points (The reference point position information is known), This method reduces the range of error, but there are also some problems. For example, it is pointed out in the literature [13] that in some cases, there is no solution when the target position is estimated according to the distance.

Location fingerprint method. The method establishes multiple reference points, collects the location (Reference point) and the corresponding RRS value or signal power information and records and stores it in the database, and obtains the position of the target point through RSS or signal power matching (K proximity algorithm, dynamic neighboring algorithm). This method mainly involves two aspects of error: first, the volatility of the RSS value or signal power affects the accuracy and stability of the collected data; second, there is an algorithmic systematic error in the RSS value or signal power matching. For the first kind of error, this paper uses the low-frequency filtering method to reduce the influence of RSS or signal power volatility, and uses data convergence as an auxiliary method to reduce the complexity of data processing. For the second type of error, the indoor positioning method based on Bluetooth and fuzzy logic type 2 [14] uses the Bluetooth beacon power as the reference quantity, and uses the fuzzy set instead of the absolute value, which enhances the data accuracy to a certain extent and the error in RSS or signal power matching is reduced, and the positioning accuracy is improved.

At present, the research work of WiFi-based passive indoor positioning technology mainly uses location fingerprints to locate, such as FILA [15], Nuzzer [16], Pilot [17]. When performing fingerprint matching, the fingerprint of the current target to be tested needs to be matched one by one with the reference fingerprint in the database, which causes problems such as excessive calculation amount, too slow matching speed in real operation stage, and low real-time performance. Secondly, the fingerprint of the reference point in the offline fingerprint database that is far away from the current position of the target may have fingerprint information similar to the target position, thereby causing interference to the fingerprint matching, so that the positioning error is increased. In view of the problems existing in the above methods, the literature [18] proposed a new location fingerprint indoor positioning method: Indoor Localization Method Based on Location Fingerprint and Range Measurement (ILLFRM). The method adds the estimated positioning in the online phase and filters the fingerprints in the offline fingerprint database that are not related to the current position of the target by estimating the positioning, so as to reduce the calculation amount in the matching process and avoid the irrelevant fingerprints' interference. At the same time, a certain amount of work is reduced, and the purpose of improving positioning accuracy and real-time performance is achieved. In the location fingerprint method, the layout of the AP has a great impact on system performance. The uneven distribution, redundancy and occlusion of indoor APs will affect the accuracy of positioning in WiFi indoors and also increase the complexity of the calculation process. For the distribution and selection of APs, literature [19] combines variance filtering, maximum average and mutual information methods, considering AP signal volatility, signal regionality and AP correlation to establish the best AP distribution strategy and improve system performance.

The selection of the reference quantity affects the performance of the entire positioning system. The data rate based indoor positioning method [20] uses the data rate as a reference quantity, since the measurement of the data rate does not require any operation of the target (Smart device) to be tested and overcomes the shortcomings of installing an application on a target mobile phone and enables passive positioning. However, the resolution of the data rate is low, the volatility is large, and the connection between the AP and the target is unstable. Therefore, the indoor passive positioning algorithm based on the data rate has a large error, and the average error is about 2 meters. Therefore, the performance of the positioning system is poor.

2 Indoor Positioning Algorithm Based on Location Fingerprint and Relative Position

Based on the above problems, this paper proposes an indoor positioning algorithm based on relative position and location fingerprint method. The rough target position determination is implemented according to the relative position-based method before the fingerprint matching, and then the RSS value fingerprint matching is adopted for accurate positioning. Specifically, the positioning method is divided into an offline phase and an online phase. The offline fingerprint database is built in the offline phase. In the online phase, the coarse positioning strategy is adopted according to the relationship model between RSS and distance. The rough position of the target is obtained (Considering that the algorithm is based on the data set, so this part is described in Section 3). Then, according to the coarse location filtering, the offline fingerprint database is eliminated, and the interference of the fingerprints that are not related to the target position in the offline fingerprint database is eliminated. Finally, the precise positioning and positioning of the target location is completed by the fingerprint matching algorithm. The flowchart of this algorithm is shown as Fig. 1.

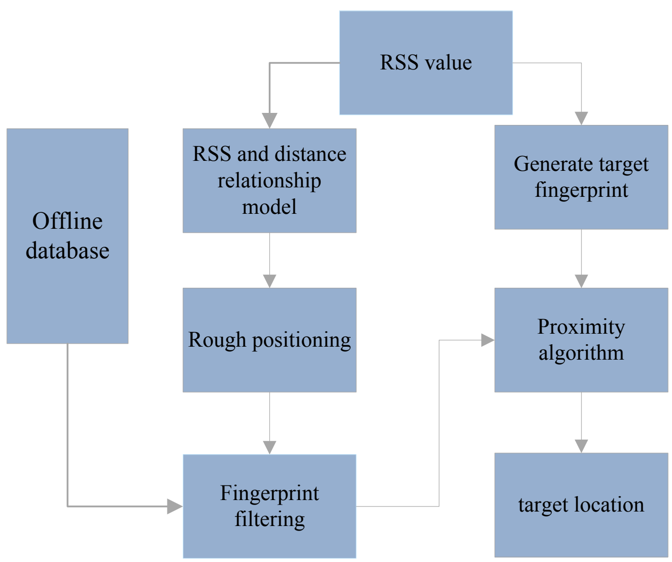

Figure 1: Algorithm flow chart

2.1 The Establishment of Offline Database

The system model used in this algorithm is shown in Fig. 2, it has a uniformly distributed reference point for use when matching fingerprints. The system is also equipped with three WiFi Pineapple routers, in which the router near the single door is the primary router and the other two routers are the secondary routers. The offline database phase only needs to make the primary router work (This method avoids the interference between the reference point and the router when the RSS value is collected, and solves the problem of route switching). The fingerprint database is built as follows: the main WiFi Pineapple is used as the signal source, and the smart device is placed on each reference point (The reference point coordinates are known), then the RSS value collected by the smart device at the point is measured. Multiple sets of data are measured, and the optimal RSS value of the point is obtained according to the data convergence and low frequency filtering method. The same method is used for each reference point and its corresponding RSS value is stored in the database. The offline fingerprint database is thus constructed.

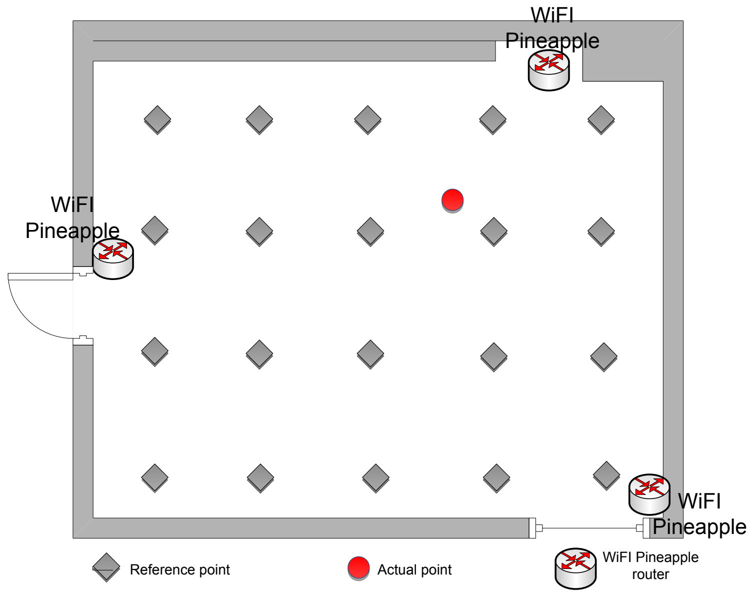

Figure 2: System model construction

2.2 Data Analysis Method

2.2.1 Data Convergence

The sequence of signal strength values at different locations can reflect the distance of the location from the signal transmission point, but the measured RSS value has volatility due to environmental uncertainties. Stable RSS is the basis and premise for establishing a model of the relationship between distance and signal strength. Therefore, it is necessary to average the signal intensity values collected for each distance point to obtain a stable signal strength mean. Of course, the more signal strength samples are collected at each distance point, the higher the stability and accuracy of the final model. However, the more samples are collected, the more work and time it takes. Therefore, a balance between cost and performance needs to be established. The data convergence method establishes a good balance point for the system.

In this paper, 40 samples were collected at different sampling points of 1 m from the ground and 3 m, 6 m and 9 m from the signal emission point. As the number of acquisitions increases, the signal strength values for each distance point are calculated separately. As shown in Fig. 3, the signal strength values at each distance basically conform to a trend, that is, the signal strength value has a certain degree of jitter when the number of measurements is small. As the number of measurements increases, the average signal strength tends to stabilize. As can be seen from Fig. 3, the optimal number of acquisitions was achieved after 20 measurements.

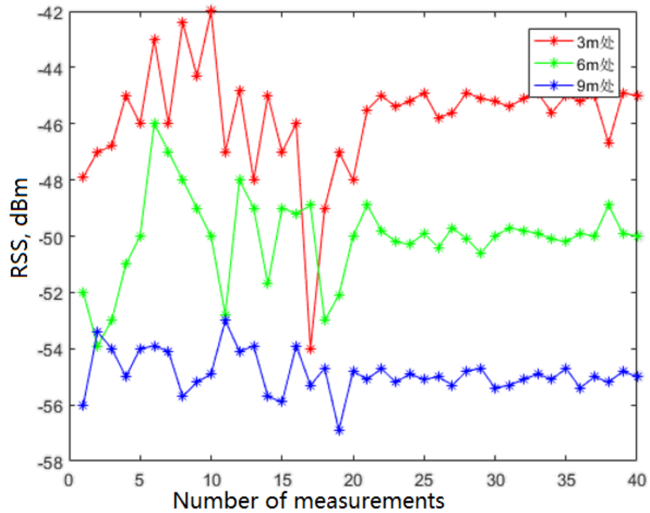

Figure 3: Convergence analysis of signal strength values

2.2.2 Low Frequency Filtering

In the above convergence analysis of the signal strength values, it has been found that the signal strength value tends to be stable after the data has been acquired for 20 times. Here, we need to discuss the distribution of the signal strength values. Here, the data collected in the convergence analysis of the signal strength values, that is, the 40 samples data collected at the distances of the signal transmission points of 3 m, 6 m, and 9 m, respectively, are collected. This is shown in Figs. 4–6 below.

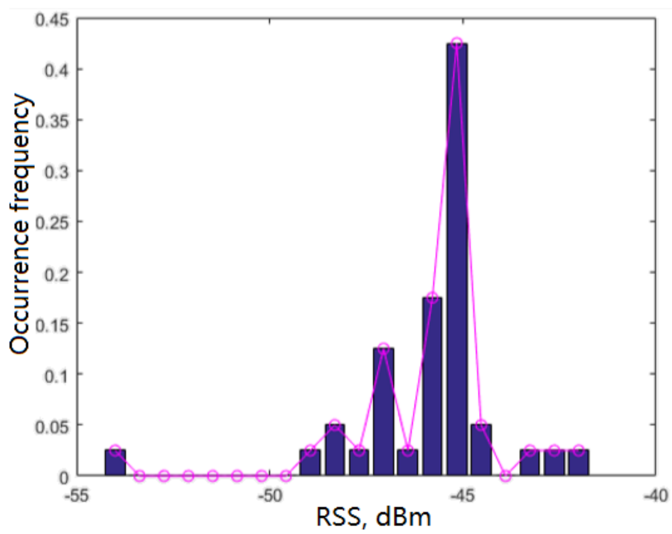

Figure 4: RSS distribution at 3m from the signal transmission point

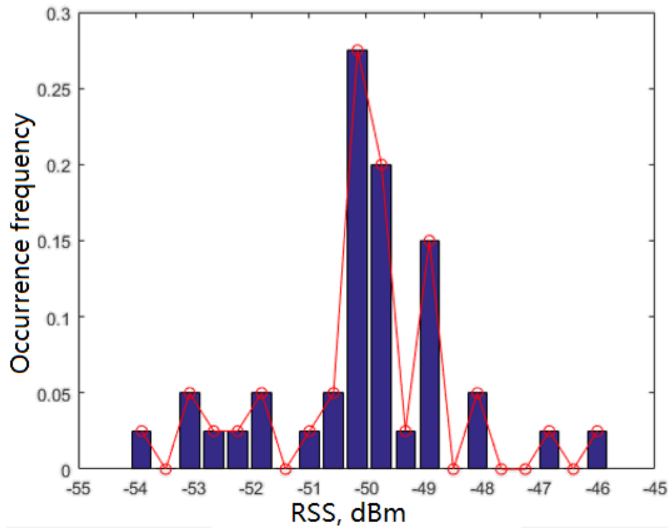

Figure 5: RSS distribution at 6m from the distance of the signal transmission point

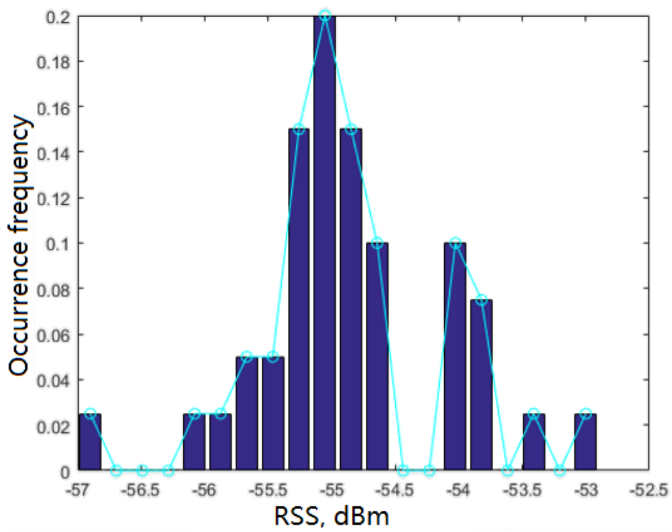

Figure 6: RSS distribution at 9m from the distance of the signal transmission point

The RSS probability distributions at 3 m, 6 m and 9 m from the signal transmission point are shown in Figs. 4–6 respectively. The mean values are –45.79 dBm, –50.05 dBm and –54.88 dBm respectively. It can be seen from Figs. 4–6 that the distribution of RSS values in a certain error range is generally similar to the normal distribution depending on the mean. The highest probability of RSS values of –44.8 dBm, –50.2 dBm and –55 dBm is 0.43, 0.28 and 0.2. Obviously, the highest probability RSS value is approximately equal to its population mean. The distribution of RSS values at other distances also mostly conforms to a similar normal distribution and will not be repeated here. It can be seen from the above analysis that some low-frequency data affect the stability of RSS, so the low-frequency filtering algorithm is adopted in this paper. That is, after filtering the data with the frequency below 0.1, the remaining data is expected.

2.2.3 Model Inversion

Since the system demand is deriving the distance based on the signal strength value and determining whether the person is indoor according to the distance, it is necessary to inversely convert the signal strength value with respect to the distance function model into a distance model with respect to the signal strength value. The experimental data is subjected to the positive filtering process shown in Fig. 7 below to obtain the arithmetic mean of the RSS at the three heights corresponding to the distance values, and the set of average values is used as the data source established by the inversion model.

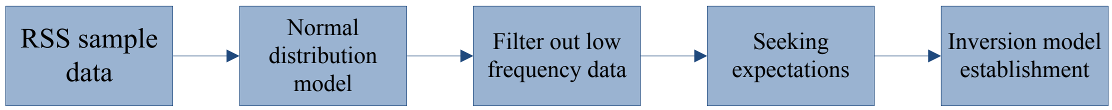

Figure 7: Normal filtering process

2.3 Rough Positioning

Rough positioning is the premise of fingerprint filtering. In this paper, the weighted centroid localization algorithm is used for coarse positioning (Three routers in this stage belong to the working state). The centroid localization algorithm takes the signal source as the center, the distance between the AP and the target to be measured is the radius, and the intersection of the circles forms the common area of the polygon. The centroid coordinate is the position coordinate of the coarse positioning. In order to further refine the coarse positioning, this paper uses a weighted centroid algorithm for coarse positioning, and sets different weights according to the contribution of known nodes to unknown nodes. With three wireless AP (WiFi Pineapple) points been set as the center of the circle O_1,O_2,O_3, if $A(x_1,y_1)$, $B(x_2,y_2)$, $C(x_3,y_3)$ is the intersection coordinate of three circles, the position of the unknown node is the centroid O of the common area ΔABC. The weighting centroid positioning principle algorithm is shown in Fig. 8 andd_1, d_2, d_3(according to the above model of RSS and distance relationship) are the distances from A, B, and C to the center of the circle O_1, O_2, O_3. The formula for solving the coordinates of the centroid$O(x,y)$ is as Eq. (1).

$$x=\frac{\frac{x_1}{d_2+d_3}+\frac{x_2}{d_1+d_3}+\frac{x_3}{d_1+d_2}}{\frac{1}{d_2+d_3}+\frac{1}{d_1+d_3}+\frac{1}{d_1+d_2}},y=\frac{\frac{y_1}{d_2+d_3}+\frac{y_2}{d_1+d_3}+\frac{y_3}{d_1+d_2}}{\frac{1}{d_2+d_3}+\frac{1}{d_1+d_3}+\frac{1}{d_1+d_2}} \tag{1}$$

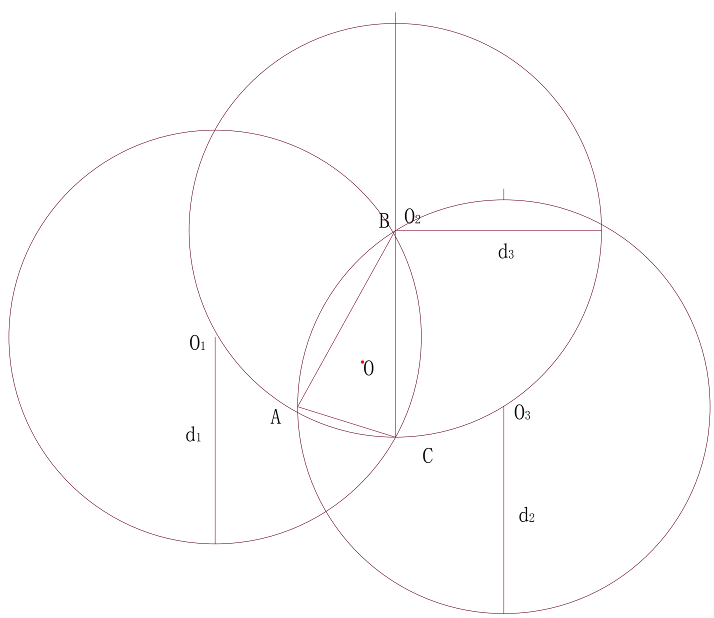

Figure 8: Principle of weighted centroid localization algorithm

2.4 Fingerprint Filtering

In order to reduce the interference caused by the fingerprint of the reference point fingerprint in the offline fingerprint database which is far away from the current target position, and the complexity of data processing, this paper proposes a fingerprint filtering strategy to filter out the fingerprint far away from the current target position. The number of fingerprint matching is reduced, the workload of data processing is reduced, and system performance is improved.

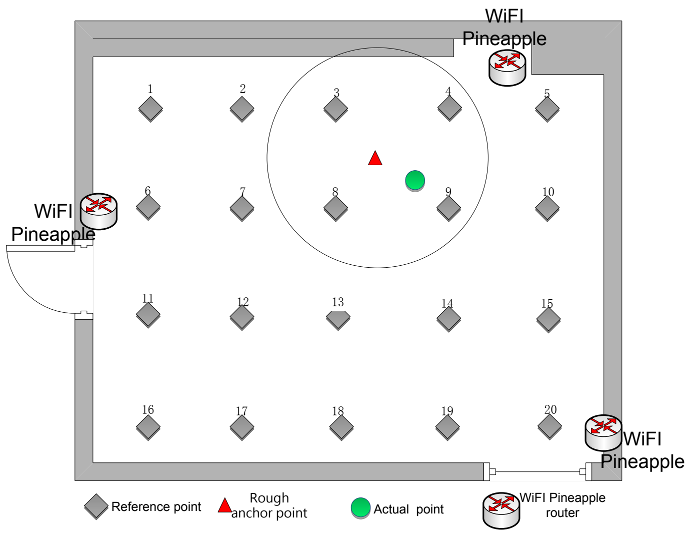

Figure 9: Fingerprint filtering demo

As shown in Fig. 9, the center of the coarse positioning target is the center, and the radius is 4 meters (This value is to be discussed) as a circle. As can be seen from Fig. 9, the reference points 1, 2, 5, 6, 7, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20 are not in the circular area, and only the reference point 3, 4 , 8, 9 is in the circular area. As a result, the fingerprints that are not in the circular area are filtered out, and the position fingerprints that are still in the circular area are retained. The radius of the circle affects the selection of the reference point fingerprint. If the radius of the circle is too large, the fingerprint filtering strategy loses its original meaning; if the radius of the circle is too small, the selected reference point fingerprint will be less, due to increasing of the positioning error. Therefore, the choice of the radius of the circle affects the performance of the whole system. Considering that the average distance between the reference points is 2 meters, this paper temporarily sets the radius of the circle to 4 meters.

2.5 Proximity Algorithm

The proximity algorithm based on the fingerprint of the reference point retained by the fingerprint filtering. Based on this, the matching strategy is performed to obtain the position coordinates of the target point. The detailed algorithm is shown in Algorithm 1.

Algorithm 1: Proximity algorithm

Input: d_i,(x_i,y_i),D

For each $i \in [1,N]$ *do*

$\Delta d_i=|d_i-D|$

End

For each $i \in [1,N]$ *do*

$$w_i=\frac{\Delta d_i}{\sum_{i=1}^{N}\Delta d_i}$$

End

$$X = \sum_{i=1}^{N} w_i \, x_i$$

$$Y = \sum_{i=1}^{N} w_i \, y_i$$

Output: (X,Y)

where D is the coarse positioning target point fingerprint, (x_i, y_i) is the reference point coordinate, d_i is the reference point fingerprint, (X, Y) is the coordinates of the target point.

3 Environmental Construction and Experimental Results

3.1 Setting up an Environment for RSS Values and Distances

Select the corridor as the experimental environment. The area is about 30 meters long. Place the WiFi Pineapple router at the entrance of the corridor and connect the WiFi signal of the WiFi Pineapple router with a smart device (Laptop). Record a stable signal strength value at a distance of one meter from the straight line. A total of 25 values are recorded to obtain 25 sets of data. Repeat the test and average the signal strength values at different distances at this height. Fig. 10 below shows the test environment plan. The office area is on both sides of the corridor. The laptop in the middle of the corridor is marked with the location of the WiFi signal receiving point. There are 25 (Not drawn), and the height of the receiving point is set separately. It is 0 m, 1 m and 2 m.

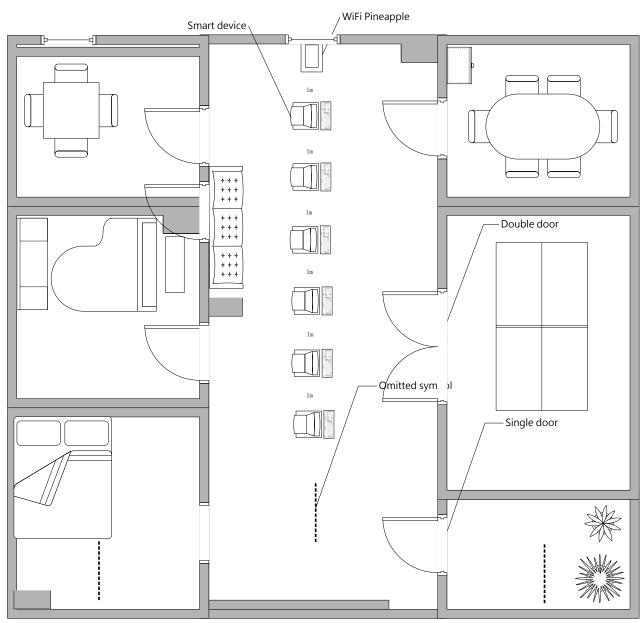

Figure 10: Experimental environment diagram

3.2 Test Process

Step 1, power up the WiFi Pineapple router at one end of the corridor and connect to the Internet port (The router is 0 meters away from the ground);

Step 2, use the pineapple router as the origin to make a horizontal line of 25 meters long, starting from the origin with a step of one meter, and recording the RSS value with a vertical height of 0 meters on this line;

Step 3, raise the WiFi Pineapple and the smart device to 1 meter from the ground to receive the signal, repeat Step 2;

Step 4, raise the WiFi Pineapple and the smart device to 2 meters from the ground to receive the signal, repeat Step 3;

3.3 Data Integration

Data integration was performed using the method described in Section2.2. The RSS value at the height of 0 mis the signal strength measured when the height of the transmission point (WiFi Pineapple) is 0m and the height of the reception point is also 0 m, and then the RSS value is averaged according to the formula Eq. (2). By analogy, this method is still used at 1, 2 meters from the ground. The result set is shown in Tab. 1 (Partial data).

$$D = \frac{\sum_{i=1}^{n} d_j^i}{n} \tag{2}$$

where j (j = 0, 1, 2 m) is the height from the ground, d_j^i is the i-th measured RSS value j meters above the ground, n is the total number of measurements, D_j is the average RSS value calculated from j meters above the ground.

Table1: Record of experimental data processing results

Distance (m)	RSS value at a height of 0 meters(dBm)	RSS value at a height of 1 meters(dBm)	RSS value at a height of 2 meters (dBm)	average value(dBm)
1	−45	−36	−55	−45.3333
2	−55	−45	−56	−52
3	−65	−44	−58	−55.6667
4	−61	−45	−61	−55.6667
5	−67	−44	−62	−57.6667
6	−68	−44	−67	−59.6667
7	−65	−48	−59	−57.3333
8	−72	−51	−62	−61.6667
9	−71	−54	−65	−63.3333

3.4 Realize Data Simulation and Fitting on MATLAB

The 25 sets of distance values in Tab. 1 and the corresponding signal intensity values at the three heights are respectively plotted as a line graph by MATLAB and the closest relational model is fitted according to each line chart. The data simulation and fitting effect are shown in Figs. 11–13.

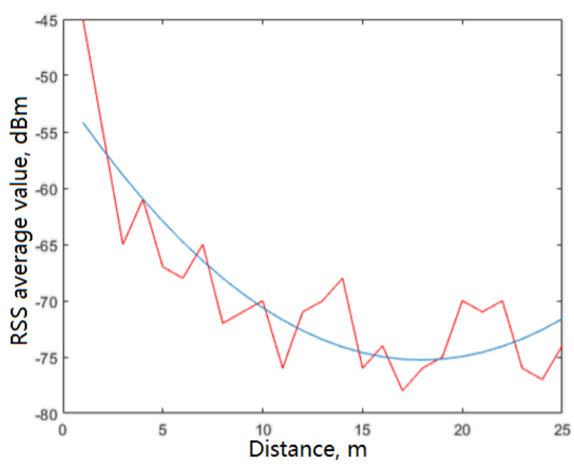

Figure 11: 0 m height simulation and fitting effect

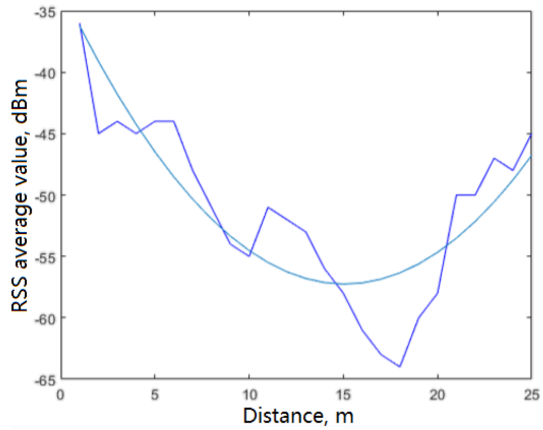

Figure 12: 1 m height simulation and fitting effect

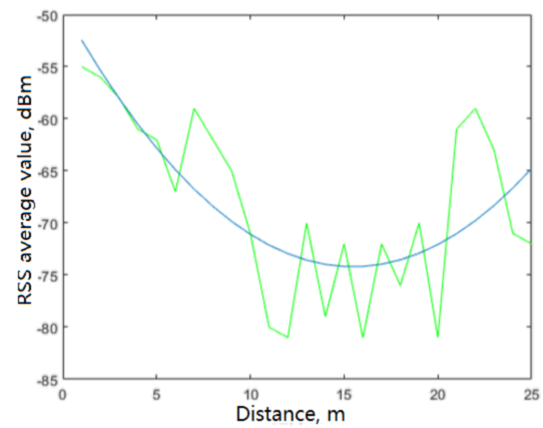

Figure 13: 2 m height simulation and fitting effect

Compare the simulation results of signal intensity at three different heights, the higher the height, the greater the fluctuation of the signal strength value, and the more sensitive the RSS is to the change in distance. As the distance is smaller than 15 meters, with the increasing of distance, the trend of the fitted image is consistent with the distance, and the RSS value is weaker.

It can be seen from the simulation diagram that the model is close to the relationship of quadratic functions:

The relationship between RSS and distance at 0 meter is as Eq. (3).

$$y = 0.0734x^2 - 2.6353x - 51.6087 \tag{3}$$

The relationship between RSS and distance at 1 meter is as Eq. (4).

$$y = 0.1062x^2 - 3.2001x - 33.1461 \tag{4}$$

The relationship between RSS and distance at 2 meter is as Eq. (5).

$$y = 0.1038x^2 - 3.2121x - 49.3443 \tag{5}$$

In view of the fact that the mobile smart device used by people usually has a height of 0–2m, the average value of the coefficients is obtained, and the relationship between the final RSS and the distance is obtained: $y=0.0945x^2- 3.0158x- 44.6997$. Because the normal person's height is less than 2 meters, most people's smart devices are within 2 meters of the ground, so the heights of 0 meters, 1 meter and 2 meters are selected to measure the RSS value. The image is easy to know, and the model is basically consistent with the experimental results.

3.5 System Performance

As shown in Fig. 14 (The part in the rectangular frame is a set of positioning results), this article only intercepted some of the positioning results. It can be seen from Fig. 14 that the algorithm optimizes the coarse positioning and improves the positioning accuracy.

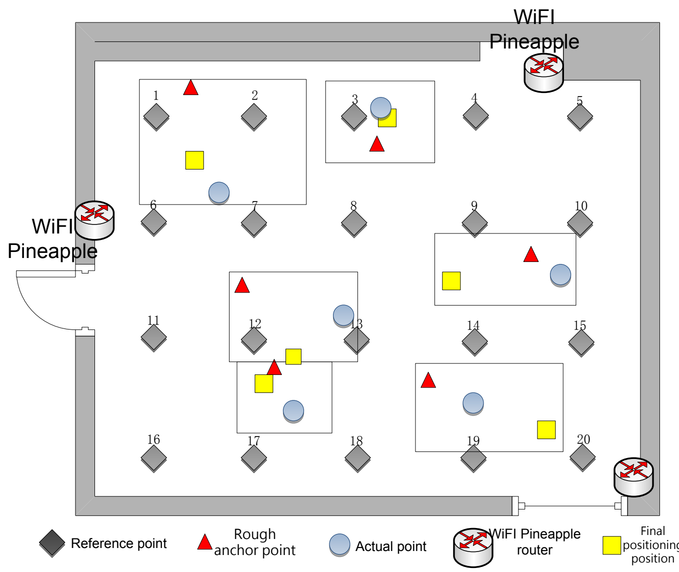

Figure 14: Test result graph

4 Summary

In this paper, the algorithm combining relative position and location fingerprint method is adopted to avoid the influence of other irrelevant fingerprints during fingerprint matching, and the matching efficiency is improved. For the relatively large data processing and RSS volatility, this paper adopts data convergence strategy and low-frequency filtering strategy to enhance the convenience and efficiency of the system.

The research in this paper also has some shortcomings. Since the selected router management website information cannot be crawled, the algorithm cannot track and locate the indoor personnel in real time. When using the weighted centroid algorithm for coarse positioning, due to the defects of the algorithm itself, there may be cases where the three circles do not intersect, that is, coarse positioning cannot be performed. Therefore, the next step will be focused on the improvement of coarse positioning, while relying on more experimental data for system optimization.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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