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A NEW INDOOR LOCATION ALGORITHM BASED ON THE Wi-Fi

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Indoor positioning technology plays an important role in people's work and life today. The relationship between modern people's clothing, food, housing and transportation and location-based service (LBS) is increasingly close, which makes the study of indoor positioning technology become a hot research topic for many scholars. In this paper, an indoor positioning algorithm based on Wi-Fi fingerprint matching is proposed. In the offline stage, by deploying a small amount of radio signal strength to locate the area, the location area selection mechanism is used to predict the location of the mobile terminal, which can avoid signal instability caused by time mobility and avoid the impact of access point (AP) facility changes. In the online stage, the positioning engine receives the real-time signal fingerprint, and matches the fingerprint to find the location. Finally, several main positioning algorithms are simulated and compared in terms of positioning accuracy. The experimental results show that when the proposed new algorithm performs Wi-Fi positioning, compared with the traditional fingerprint positioning algorithm, the positioning accuracy is improved.

Keywords: Location Based Service, location accuracy, Indoor positioning technology

1. Introduction

In order to solve the problem of location accuracy degradation caused by different intelligent terminal positioning in Wi-Fi fingerprint, the literature [1,2] studied the improvement effect of the improved weighted K nearest neighbor algorithm (WKNN) that replaced the Euclidean distance with gray correlation degree. Both accuracy and universality have been greatly improved. Literature [3,4,5] uses ZigBee technology to collect specific fingerprint signal strength (RSSI) values, establishes an offline fingerprint map database, and then obtains the predicted location of unknown nodes through related online matching algorithms, and uses linear relationships to gradually approach the real coordinates to make indoor positioning accuracy improved effectively. Literature [6,7] uses limiting and moving average filtering to preprocess the database optimization and allocates the area number of the sampling point according to the indoor environment to build a multi-dimensional fingerprint database. The optimization of the matching algorithm firstly classifies the positioning points

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according to the support vector machine (SVM) [8,9], obtains the corresponding area number, and then combines the Euclidean distance, the Manhattan distance and the Chebyshev distance to obtain a position estimate. Combined with the pedestrian dead reckoning (PDR) algorithm [10,11], the obtained step length and heading angle are combined with particle filtering (PF) to achieve positioning and improve positioning accuracy [12].

Literature [13,14] proposed an improved weighted K-nearest neighbor method (WKNN) combined with the maximum entropy volume integral Kalman filter (MCCQQKF) WIFI indoor positioning method. This method improves the WKNN positioning algorithm, adopts Mahalanobis distance as the measurement method of distance in WKNN, and then calculates the degree of difference in the signal value of the access point, and uses it as the weight parameter of the Mahalanobis distance between the moving target and the reference point. The weighted distance is used to weight the position of the reference point to estimate the position of the moving target. MCCQKF is obtained by introducing the maximum entropy criterion into CQKF, and the MCCQKF algorithm is used to filter the positioning results obtained by the improved WKNN, which effectively improves the positioning accuracy [15,16].

In order to improve the indoor positioning accuracy and stability of the WIFI signal multipath effect on the received signal strength, the document [17-19] proposed to divide the positioning site into the same size area block in the offline stage and use the adaptive variance compensation at each connection point. The Kalman algorithm filters the original data [20,21]. Then use the K-Means algorithm to classify the filtered data, and use the processed (Channel State Information, CSI) [22-24] amplitude and phase information together as a fingerprint; In the online phase, the real-time data collected from the point to be measured is matched and identified with the fingerprint library, and the positioned object does not need to carry any equipment. Using the sub-carrier characteristics in the channel state information for positioning can effectively reduce the influence of multipath attenuation at the signal receiving end, and the positioning accuracy is significantly improved. Literature [25-27] uses median filtering to denoise the CSI amplitude in the offline training phase and uses linear transformation to calibrate the CSI phase [28,29]. The processed amplitude and phase are used as the original joint fingerprint, and the improved K-means algorithm is used to the joint fingerprint set of each reference point is divided into multiple sub-data sets to describe the multipath characteristics of the location, and the Principal Component Analysis (PCA) algorithm of high-dimensional data clustering is used to extract the features of the sub-data sets to reduce redundancy information, improve the distinguishability of fingerprints at different locations, and finally use feature fingerprints to train a Generalized Regression Neural Network (GRNN) model. In the online phase, the trained GRNN model is used to predict the position of the target object on the online measured CSI data, and the positioning accuracy is significantly improved [30].

Although the RSSI localization algorithm which has already existed can well handle the noise of the Gaussian distribution, however, there are some studies have shown that indoor environment Wi-Fi signal propagation exists multipath effect and non-line-of-sight propagation, affect the positioning accuracy, this paper raises a new Wi-Fi fingerprint localization algorithm to establish the fingerprint model, through radio frequency fingerprint acquire offline training in the space position. This paper designs the propagation loss model, the probabilistic fingerprint positioning model, calculate the target node position, for the feasibility and precision inspection system, the tester makes Android smartphone millet 6 a was used as hardware platform installation indoor positioning system, and carries on the analysis and comparison with the result of the experiment data, the positioning precision is improved.

2. Model

A wireless access point (AP) is a networking device that allows Wi-Fi to connect to a wired network. Access points act as key transmitters and receivers of wireless radio signals. Radio map (RP) generally refers to the power spectral density of geographical signals superimposed by concurrent wireless transmissions as a function of position, frequency, and time.

The indoor positioning technology based on Wi-Fi fingerprint is mainly divided into two stages. Offline stage: The purpose is to build an RSSI fingerprint database, which is a list of RSSI indicators from various AP at a certain point. In the offline phase, AP and Radio Map (RP) nodes need to be arranged in the environment first, which can be uniformly deployed or randomly thrown. Then simultaneously collect fingerprints at each RP point to build a fingerprint database. Assuming that there are r RP nodes and a AP node in the environment, the *i* RP in the scene receives the RSSI from the j AP, which can be expressed as $RSSI_{IJ}$.The fingerprint database will be used for query purposes in the online phase - Online stage: Collect RSSI indicators from each AP at the point to be located, so as to construct the fingerprint vector of the current position, and put this vector into the offline fingerprint database for matching. According to the matching of fingerprints, several similar fingerprints are selected from the fingerprint database and the final position is further determined. The positioning process of the target node is shown in Fig.1.

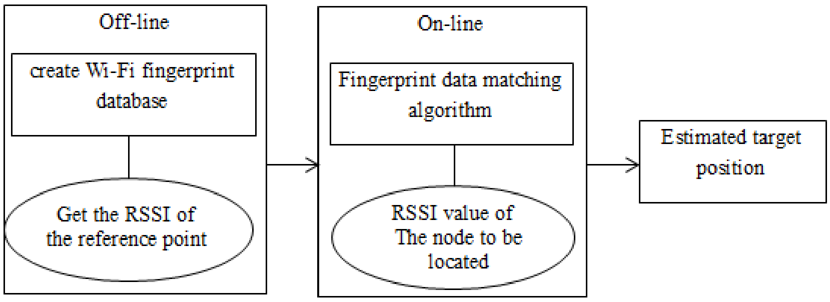


Fig.1. The process of target localization

2.1 Propagation loss model

The propagation loss model method is to use the loss in the signal propagation process to establish a model, and then estimate the distance from the transmitter to the mobile end; After the coordinate information of the signal transmitter is obtained, the position coordinates of the mobile terminal are estimated by crossing the signals of multiple transmitters.

The establishment of the propagation loss model is the difficulty of this method, because the model error will directly affect the error of the distance estimation result, and then affect the error of the final positioning result. Ideal conditions, that is, ignoring the reflection, refraction, scattering and other phenomena in the process of signal propagation, the signal attenuation on the propagation path is only related to the distance, the basic model is as formula (1):

$$P(dBm) = p_0(dBm) + 10nlg(d/d_0) \tag{1}$$

Among them, P is the real-time power when the distance between the transmitter and the mobile terminal is d, P_0 refers to the power at the reference distance d_0, n refers to the path loss factor, and the value of n is determined by the performance of the propagation medium. However, the actual indoor space is often more complex than the outdoor space, and the signal propagation path becomes more complicated. Taking the blocking factors such as doors, windows and walls into account in the loss model, the propagation model can be improved to formula (2):

$$P(dBm) = p_0\left(dBm) + 10nlg\left(\frac{d}{d_0}\right) + WAF + \varphi\right) \tag{2}$$

Among them, WAF is the loss value when the signal penetrates the obstacle, its values are shown in Table 1, φ refers to white Gaussian noise.

Table 1

AP signal obstacle penetration loss

No.	name	5Ghz path loss
1	PVC plate	0.6dB
2	Gypsum plate	0.7dB
3	Plywood	0.9dB
4	Gypsum wall	3.0dB
5	Rough chipboard	2.0dB
6	Veneer board	2.0dB
7	Glass plate	2.5dB
8	6.2cm Sound proof door	3.6dB

2.2 Probabilistic fingerprint localization model

Naive Bayesian is an implementation of Bayesian classification based on the Bayes theorem in mathematical statistics, using prior knowledge in statistical classes and new evidence in experimental data to predict the likelihood of class membership. Using the Naive Bayes method to achieve indoor positioning, the essence is to obtain the posterior probability of the real-time RSSI position fingerprint samples of each node in the positioning space. Naive Bayes has a default condition that different APs are independent of each other.

Assuming that there are m position fingerprints ($\{G_{1,2},\ldots,G_m\}$)in the indoor positioning space, the fingerprint data of each sample point corresponds to its position $\{M_1, M_2, \ldots, M_m\}$ one-to-one. In the online positioning stage, the RSSI of each location fingerprint sample is the average RSSI of n APs, denoted as S,$S=\{s_1,s_2,\ldots,s_n\}$.From this, Naive Bayes can be represented by P ($L_i|S$).By Bayes' principle, the posterior equation can be transformed as follows:

$$P(L_i|s) = \frac{P(S|L_i)\cdot P(L_i)}{P(s)} = \frac{P(S|L_i)\cdot P(L_i)}{\sum_{k\in L} P(S|L_k)\cdot P(L_k)} \quad (3)$$

Among them, P(S|Li) is the conditional probability of the RSSI location fingerprint sample S measured in real time corresponding to the online stage of the known node i,P(Li) is the prior probability at the position Li in the positioning space, based on the same probability of the target appearing at different positions, so it obeys a uniform distribution. In the above formula, the probability of obtaining the position fingerprint S for the position can be calculated by formula (4), $P(S_n|L_i)$ is the probability that the RSSI value of the mth AP measured at position L_i is Sn, and its probability density function is shown in formula (5),μ and σ are the mean and standard deviation of the RSSI value of this AP respectively; since the reference points in the positioning area are randomly deployed, the probability $P(L_i)$ of the selected position L_i obeys a uniform distribution.

$$P(S|L_i) = P(S_1, S_2, \cdots, S_m|L_i) = P(S_1|L_i) * P(S_2|L_i) * \cdots * P(S_m|L_i) \quad (4)$$

$$P(S_n|L_i) = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left[\frac{(S_n-\mu)^2}{2\sigma^2}\right] \tag{5}$$

2.3 Calculate the target node location

The clustering algorithm optimizes the classification of location nodes based on the Support Vector machine (SVM), obtains the corresponding region number, and then combines Euclidean distance, Manhattan distance and Chebyshev distance to obtain the location estimation.

After the clustering is completed, K representative sub-data sets are obtained from the n groups of original fingerprint sets Raw, including amplitude and phase, the sub-dataset C composed of the output K cluster centers is

$$C = [C_1, C_2, \cdots, C_A]^T \tag{6}$$

In formula (6), $C_K = [A_K, P_k]$ is the cluster center of the Kth class. Since the original fingerprint set Raw is an n*D numerical matrix, where $D = T_X * R_X * N * 2$, and '2' represents two parameters of amplitude and phase, n is the number of samples. The original fingerprint set Raw is divided into K sub-data sets C by a clustering algorithm, that is, C is a dimensional numerical matrix.

Calculate the fingerprint similarity between the target node and all RPs. In the existing sample dataset fingerprint database, the storage information format of the fingerprint sample is $RSSI_i = (rssi_1^i, rssi_2^i, \ldots, rssi_m^i)$, let the position information data of the node to be located be RSSI, and the format is the same as that of the fingerprint in the fingerprint database. The candidate RP with the highest similarity is selected, and the weights are randomly initialized for the RP.

$$d_i = \sqrt{\sum_{i=1}^{n} (RSSI_i - RSSI_I)^2} \tag{7}$$

The Euclidean distance d_i between the fingerprint sample in each database and the sample to be located can be obtained by formula (7). Ideally, the fingerprint sample corresponding to the smallest d_i should be the closest to the sample to be tested. The high dependence of a single fingerprint may lead to the low robustness of the indoor positioning system using this positioning method. The final positioning result is easily affected by noisy data, resulting in large errors. The first K most similar samples are selected, and the result is predicted in the form of the mean.

The target model is established so that the fingerprint feature of the candidate RP can obtain the optimal weight of the fingerprint feature of the target node.(x_i, y_i) is the fingerprint feature vector of the target node,$RSSI_i$ is the fingerprint feature vector of the ith candidate RP.

$$(x_i, y_i) = \left(\frac{\sum_{k=1}^{K} x_k}{K}, \frac{\sum_{k=1}^{K} y_k}{K}\right) \tag{8}$$

Based on the above considerations, the weight coefficient ω of the location fingerprint in predicting the location is introduced, the weight coefficient ω is the proportion of the K position fingerprints in the estimated position. The simplest calculation method is that the larger the Euclidean distance d_i, the smaller the weight coefficient ω.Here ω is taken as the reciprocal of d_i. Considering that d_i may be 0, a very small number ε should be added to the denominator.

$$\omega = \frac{1}{d_i+\varepsilon} \tag{9}$$

Next, calculate the weighted contribution of each of the K fingerprints:

$$(x_{wk}, y_{wk}) = \omega(x_k, y_k) \tag{10}$$

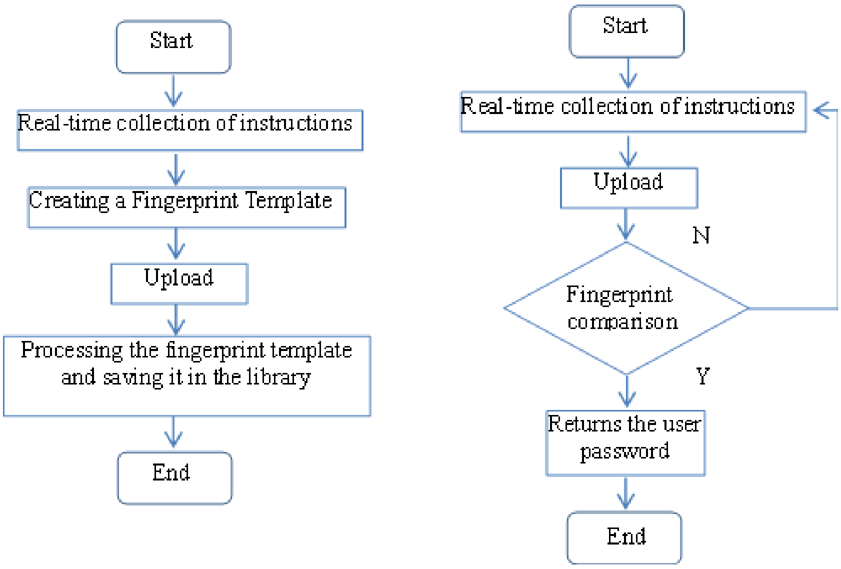
The weighting is the difference of the RSSI signal contribution of the nearest neighbor K sample reference points, the method of assigning different weights to reference points at different positions according to the Euclidean distance, and then obtaining the position coordinates of the target point to be measured. The method of assigning weights is based on the Euclidean distance between the RSSI of the sample reference point and the RSSI measured in real time by positioning. The larger the distance, the smaller the weight, and vice versa, the greater the weight. Bring in formula (8) to obtain the calculation formula for calculating the final position estimation coordinates of the target node, such as formula (11):

$$(x,y) = \sum_{j=1}^{k} \frac{\rho}{d_i+\varepsilon}(x_i, y_i) \tag{11}$$

Where ρ refers to the normalized weighting coefficient, ε refers to the smaller parameter value. To prevent the denominator from being zero, the K nearest neighbor sample reference points are weighted and averaged, which can improve the accuracy of the positioning system to a certain extent.

2.4 The flow diagram of the proposed algorithm

The basic idea of Radio frequency fingerprint positioning algorithm is to establish an offline database first, and then match the fingerprint to be positioned and collected with the fingerprints previously stored in the fingerprint database. The fingerprint acquisition stage is responsible for data samping, data collection, data management and organization are used to establish the fingerprint database, as shown in Fig. 2(a). The fingerprint comparison phase collects fingerprints and compares them with those in the fingerprint database, as shown in Fig. 2(b).The online positioning stage is responsible for receiving real-time fingerprint observation and positioning using historical location data. Login to AP is verified by using the username and SSID, and the algorithm can be used in smartphones.



(a)Fingerprint Collection (b) Fingerprint comparison

Fig.2 The flow diagram of the proposed algorithm

3. Experiment and analysis

3.1 Environment

In order to test the feasibility and positioning accuracy of the system, the testers used the Android smartphone 6A as the hardware platform to install the indoor positioning system and conducted the test on a 12 m × 14 m site on the 6th floor of Building A of the school. Fig. 3 shows the experimental site and location fingerprint collection points.

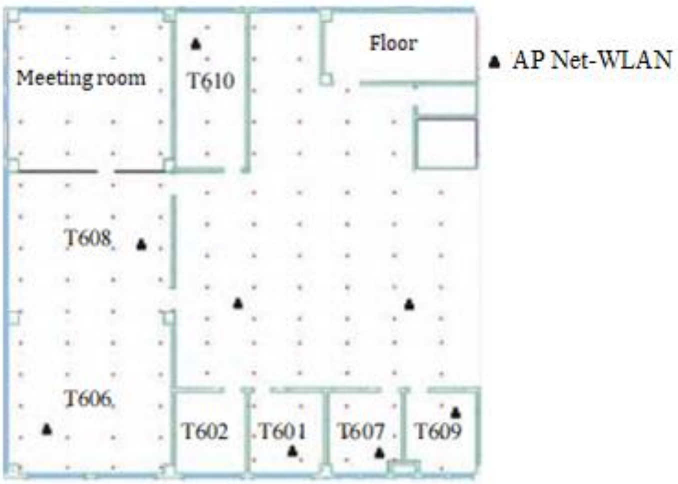


Fig. 3 Experiment site plan and location fingerprint collection point

In the test site, in order to prevent the data redundancy caused by the large number of location fingerprints and affect the positioning speed and accuracy. The tester collects a location fingerprint every 1 m by holding a mobile terminal, and a total of 145 location information are collected. The location fingerprint distribution is shown in 3. After the collection is completed, it is stored in the location fingerprint database of the database side. The five AP signals scanned at the location coordinates (423.213, 156.480 8) of the floor plan when the fingerprint collection point is located are shown in Table 2, these addresses are relative.

Table 2

AP Information

No.	Position Coordinate	Network adders	MAC adders	RSSI/dBm
1	(423.213,156.480 8)	606	48:0e:ec:a6:15:b0	-55
2	(423.213,156.480 8)	608	48:0e:ec:a6:15:f0	-56
3	(423.213,156.480 8)	610	d1:0e:23:a6:90:12	-58
4	(423.213,156.480 8)	601	ae:ae:09:12:e5:10	-60
5	(423.213,156.480 8)	Net-wlan	45:12:e3:f6:05:c0	-61

3.2 Performance Analysis of Algorithms

When the k value is different, the process is realized, and the parameter changes are shown in Table 3.

Table 3

Variation of each parameter in the positioning process

K	Euclidean distance of the point to be measured	Weights	Fingerprint location	Weighted value
1	7.4095552466790915	0.20988085626265646	(264 341)	(55.40854605 71.56937199)
2	8.1984055841707	0.18968708881693475	(10 363)	(1.89687089 69.85641324)
3	9.09622295905895	0.1709655395844076	(748 298)	(127.822361 50.9477308)
4	10.448445505471735	0.1488407235111326	(552 453)	(82.16007938 67.42484775)
5	10.75373265253996	0.14461557597911898	(275 108)	(39.76928339 15.61848221)
6	11.419128599273623	0.13607021584574966	(245 658)	(33.33720288 89.53420203)

Different weights are assigned to the fingerprint node according to the Euclidean distance. The farther the location is from the target node to be located, the less influence the location has on the target node. Therefore, the smaller the weight coefficient is.

3.2.1 Performance simulation of RSSI ranging and positioning technology

The indoor positioning algorithm based on location fingerprint is divided into two stages: database establishment stage and position estimation stage. The root mean square error (RMSE) is calculated as formula (12), which measures the deviation between the observed value and the true value.

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(\hat{y_i} - y_i)^2} \tag{12}$$

The measured value of RSSI is generated by the logarithmic path loss model. In order to reduce the error caused by fluctuation, its value can be obtained by averaging multiple measurements. The reference distance path loss and path loss factor in the logarithmic path loss model can be estimated from measurements of the reference points relative to each other. Complete the RMSE curve comparison diagram between the ideal case (known reference distance path loss and path loss factor) and the actual case. The abscissa is the noise variance, and the ordinate is the Root Mean Square Error (RMSE). The RMSE can measure the deviation between the observed value and the true value, as shown in Fig. 4.

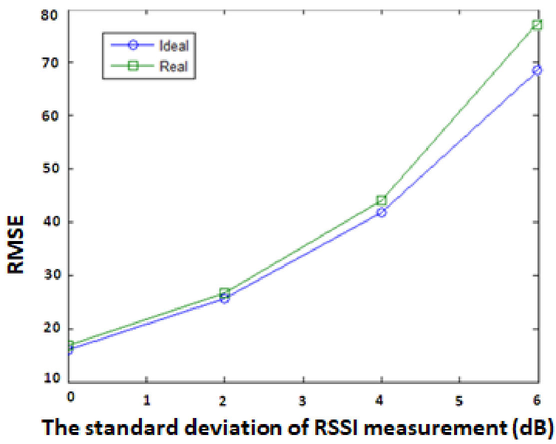


Fig. 4 Comparison of RMSE curves under ideal and actual conditions

3.2.2 Comparison and simulation of CDF curves of several different algorithms

The establishment of the location fingerprint database is based on the grid form to generate different fingerprint nodes, shown in Fig.5.

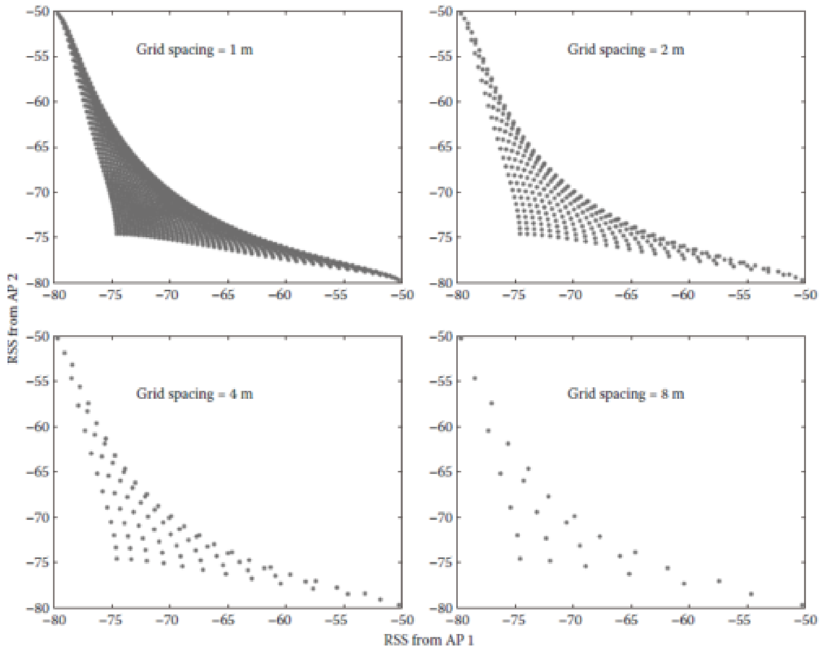


Fig.5. Representation of individual fingerprints in a grid-divided region in a signal space

In this paper, support vector machine (SVM) method is used to select clustering. Comparing the CDF curves of the nearest neighbor (NN) algorithm, KNN algorithm and New-FR algorithm, the abscissa is the positioning error, and the ordinate is the CDF, as shown in Fig.6.

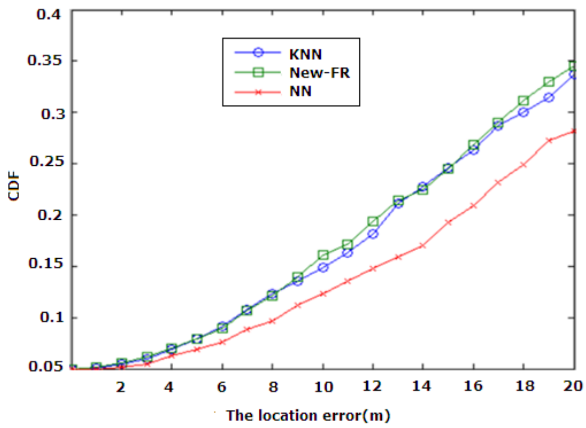


Fig.6. Comparison of CDF curves of NN algorithm, KNN algorithm and New-FR algorithm

It can be concluded from the above figure that the fitting of KNN and New-FR algorithms is better than that of NN, and the probability of identifying in an area is higher, and the positioning accuracy is higher. The cumulative distribution function (CDF) is the integral of the probability density function, which can completely describe the probability distribution of a random variable X. As the positioning error gradually increases, the advantages of KNN and New-FR are highlighted, and the CDF probability curve distribution is more obvious, which means the more accurate the positioning.

3.2.3 Difference Comparison of Error Accumulation

Comparison of Location Errors of Different Positioning Algorithms the NEW-FR algorithm has better Location positioning accuracy than other algorithms. The cumulative errors of NN, KNN4, Bayes and NEW-FR experiments are 2.0813 m, 1.3958 m, 1.9554 m and0.835029 m, respectively, shown in Fig.7.

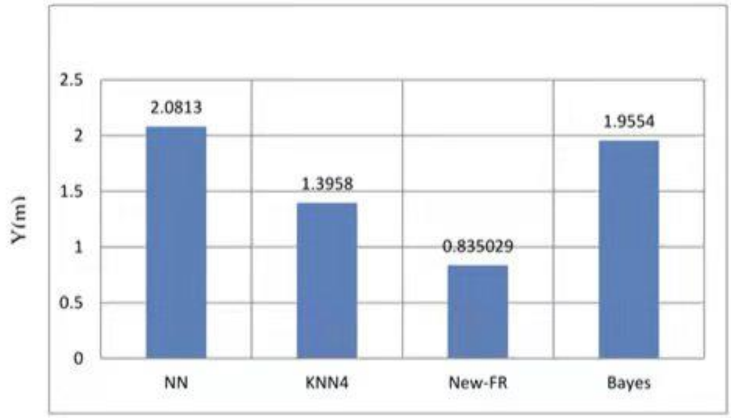


Fig.7. Comparison of Location Errors of Different Location Algorithms

4. Conclusion

In this paper, an indoor positioning algorithm based on Wi-Fi fingerprint matching is proposed. In the off-line stage, by deploying a small number of radio signal strength location areas, the design is based on the signal propagation loss model, and the location area selection mechanism is used to predict the location of mobile terminals, to avoid the error caused by the change of access point (AP) facilities. In the online stage, a probabilistic fingerprint location model is designed to match the fingerprint to find the location. Finally, several main positioning algorithms are simulated and compared in terms of positioning accuracy. The experimental results show that the proposed new algorithm for Wi-Fi fingerprint positioning improves the positioning accuracy compared with the traditional fingerprint positioning algorithm.

The follow-up research direction is mainly to find other more effective and stable information to replace the signal strength information, and research to add other information for positioning assistance to improve the positioning accuracy.

Another example is to start work from the existing single-point positioning to the multi-point trajectory positioning direction.

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