

A Wireless Fingerprint Location Method Based on Target Tracking

Xu Han

School of Information and Electronics
Beijing Institute of Technology
Beijing, China
E-mail: hanxu@bit.edu.cn

Zunwen He

School of Information and Electronics
Beijing Institute of Technology
Beijing, China
E-mail: hezunwen@bit.edu.cn

Abstract—With the popularization of wireless networks, wireless positioning technology is used to locate the location of the target location. The rapid development of wireless location technology satisfies people's demand for positioning services. How to use existing equipment to improve positioning accuracy is particularly important. At present, most of the indoor positioning methods are based on the received signal strength fingerprint recognition algorithm. This algorithm establishing a fingerprint database of the location area signal strength, it matches the real-time collected signal strength. To achieve the purpose of location estimation. This paper first studies the accuracy of wireless fingerprint location using KNN classification algorithm and compares it with other positioning of fingerprint localization algorithms such as SVM, logistic regression and random forest. Finally, the target tracking algorithm is used to process the positioning result of the RSS based WIFI indoor positioning algorithm KNN in the indoor scene, and the trajectory analogy is given. The results show that compared with the traditional KNN algorithm, this method can effectively improve the positioning accuracy of about 20%.

Keywords: location fingerprint location, RSS, target tracking

I. INTRODUCTION

In recent years, with the rapid development of wireless mobile communication technology, the demand for position sensing services in indoor scene is increasing day by day. The GPS satellite navigation and positioning system cannot be applied to indoor environments, so it is necessary to use other technical means to achieve indoor positioning. The indoor environment is complex and changeable. Usually there are many building walls, interior decoration, personnel, etc. At the same time, the propagation of wireless signals in indoor enclosed areas will have different effects in different environments, this will cause very high positioning accuracy. The large impact, the instability of signal propagation is also a major problem facing wireless positioning technology. At present, typical hardware devices for indoor positioning include Bluetooth, RFID, ultra wide-band, ZigBee, sensors, LED visible light. The positioning system based on such devices has high positioning cost and difficult to popularize in practical applications. Wi-Fi is widely distributed in large indoor places such as homes, shopping malls, subways, and stations, all this place has integrated Wi-Fi modules for mobile phones, computers, and various terminal devices [1]. Wireless access points (APs) have a wide coverage, and Wi-Fi based indoor positioning technology has become a hot research issue.

At present, in the Wi-Fi based indoor positioning technology, the method for receiving signal strength is often used, and the RSS based method can be further divided into RSS ranging positioning and position fingerprinting. The idea of ranging positioning is to estimate the distance between the intelligent terminal and the AP according to the

propagation loss model of the space in RSS. According to the trilateration method, also the position of intelligent terminal can be calculated.

However the problems of refraction, scattering and multipath fading in the indoor propagation of Wi-Fi signals, the method based on RSS ranging is difficult to meet the positioning accuracy in practical applications. The location fingerprint method has been studied by many scholars at home and abroad. According to the different position fingerprint representations in the database, the location fingerprint location technology based on received signal strength is divided into two categories: The first type is deterministic positioning method. The location fingerprint of the method is the average of the signal strength of each access point, and the value is used to estimate the user location using a deterministic reasoning algorithm. For example, Microsoft's Bahletal. use the signal space nearest neighbor method and the KNN method in the location fingerprint. One or more samples closest to the real-time signal strength samples are found in the database, and the average of their corresponding sampling points or multiple sampling points is taken as the estimated user position [2]. Based on KNN, the literature proposes two strategies for determining weighting coefficients for multiple candidate positions [3].

The second type probability-based localization method, which establishes a model by using conditional probability as a positional fingerprint and uses a Bayesian inference mechanism to estimate the user's position [4]. Two methods for estimating the conditional probability distribution function or likelihood function are given in kernel method and histogram method [5]. In the kernel method, the probability of each measured sample is represented by a Gaussian kernel function. Histogram method The probability density function is a piecewise constant function, which divides the signal strength into several intervals between the minimum and maximum values, and counts the number of occurrences of signal strength in each interval. The famous RSSI position fingerprint positioning system has Microsoft. Developed RADAR system and Harvard University MoteTrack positioning system [2]. At present, the main goal of indoor positioning is how to improve the positioning accuracy.

II. POSITIONING TECHNOLOGY BASED ON LOCATION FINGERPRINTS

Positioning techniques are based on wireless signals for indoor environments: TOA, TDOA, AOA, and techniques based on received signal strength. Because the signal transmission loss models in different environments are different and interfered by many factors, it is very difficult to establish an accurate signal transmission loss model suitable for the real-time environment [6]. The location fingerprint location technology based on the above mentioned situation

is more suitable for complex indoor environments, and has been widely studied and adopted. This technique is used in this paper.

The location fingerprint establishes location fingerprint database according to the signal strength values received at different actual locations, and the location corresponding to the information closest to the actual measured signal strength value in the wireless fingerprint database space during positioning is the user location[7]. Another positioning methods, multipath propagation non-line-of-sight(NLOS), and multiple access propagation are the main causes of positioning errors, but position fingerprinting technology uses multipath propagation to construct position information. In the process of wireless signal propagation, it is disturbed by the environment and obstacles. For each location, the multipath structure of the channel is unique, and its multipath feature can be considered as the fingerprint of the location [8].

The basic idea of location fingerprint localization algorithm: discretize the localization region, collect the RSS information of each discrete point, extract the feature vector of rss as the unique fingerprint information, construct a location fingerprint database according to the feature vectors of all discrete points, and the actual Physical locations are mapped one by one, also known as training sets. During the positioning, the matching algorithm is used to find the position in the fingerprint database that has the highest similarity with the feature to be located RSS.

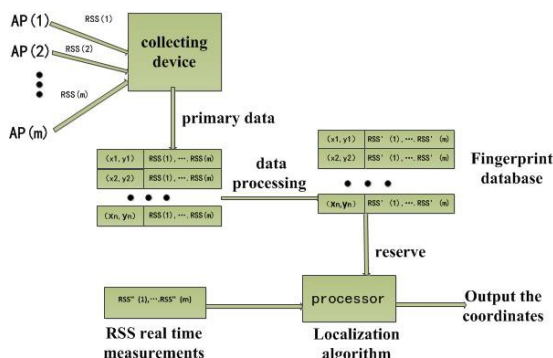


Fig.1.Fingerprint-based indoor positioning schematic

The implementation of the location fingerprint location algorithm is generally divided into an offline acquisition phase and an online matching phase.

Offline acquisition phase: collect feature information of each fixed point in the location area, and establish an offline database of location fingerprints. First, draw a map of the location area, and use the mesh to determine a reasonable reference point. Finally, measure the RSS values of the reference APs from different APs (average multiple measurements) and record them in the database. The database is the location offline fingerprint database. The size of the training data set determines the positioning accuracy. However, as shown in the following figure, when the number of data in the training data set exceeds 5000, the positioning accuracy is increased when the number of collected data is increased, so it can be based on the needs of the positioning scene.

Decide to train according to the size of the collection, the workload of data collection is reduced.

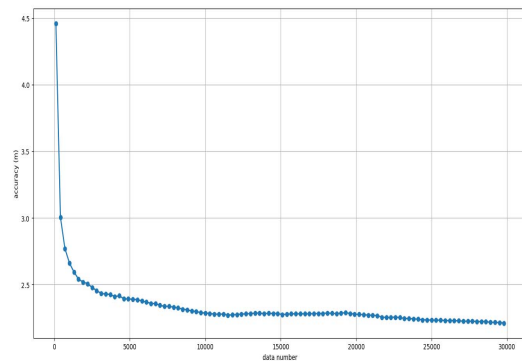


Fig.2. Training data volume and accuracy curve

Online matching phase: When the device under test is in the current location area, in order to determine the location of the test point, the corresponding matching algorithm needs to be selected. There are usually two types of location fingerprint based positioning. One is to determine the position by comparing the signal characteristics and the pre-calculated statistical values in the fingerprint database. Another method is to calculate the signal characteristics and the possibility in the fingerprint database.

The matching algorithm used in the real-time positioning phase during the positioning process is the key to the positioning accuracy. There are usually two types of positioning algorithms based on RSS location fingerprints. One is deterministic algorithm that compares with signal characteristics pre-calculated statistical values in the fingerprint library. The other is a probabilistic algorithm that calculates the likelihood that a signal signature belongs to a distribution (stored in a fingerprint library). For the above two methods, how to select according to the actual application scenario, the simple disadvantage of the deterministic positioning method is that the calculation amount is large, and the probability based method reduces the calculation amount, but the precision has no deterministic method and the parameters are more. A large number of samples are needed to calculate the parameters. kNN is a simple supervised machine learning algorithm that selects the position of the k fingerprints closest to the current RSS to estimate the current position. It is simple, intuitive and effective. Based on this paper, the KNN method is chosen for high precision [9].

KNN finds the k samples closest to the signal strength samples received by the points to be located in the location fingerprint set, and averages the position coordinates of the k fingerprints to obtain the positioning result. How to choose the optimal hyperparameter k is the key to reduce the computational efficiency of the algorithm. By preprocessing and cross-validating the data, the relationship between the hyperparameter k and the scores is plotted. It can be seen that k usually takes an integer less than 20.

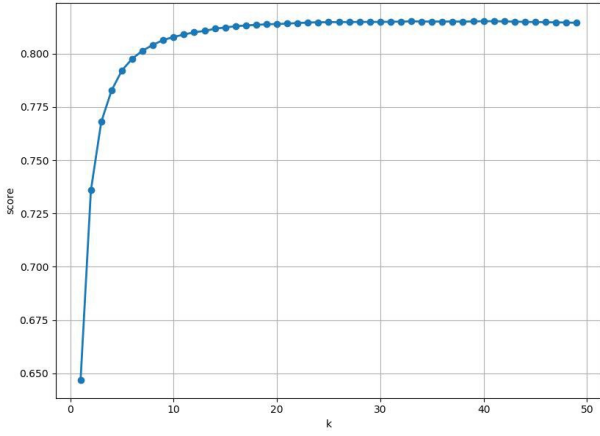


Fig.3. Curve of hyperparameter k and score

With the research on fingerprint location, how to improve the positioning accuracy based on the existing matching algorithm has become a hot topic in this field. This paper proposes a method to combine the machine learning model with the target tracking algorithm.

When locating tracking, first obtain a position estimate (observation position) by position fingerprinting method (assuming that the moving target is uniform motion), the current position (predicted position) can be predicted from the position and velocity of the previous moment, and then the observation result. And the predicted result is a weighted average as the final positioning result. If the prediction process and the observation process are both linear Gaussian, the weighting by Kalman is the optimal result. The magnitude of the weight depends on the observation position and prediction. The degree of uncertainty in location [10].

$$\hat{\mathbf{x}}_k^- = A\hat{\mathbf{x}}_{k-1} + B\mu_{k-1} \quad (1)$$

$$P_k^- = AP_{k-1}A^T + Q \quad (2)$$

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (3)$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + K_k (z_k - H\hat{\mathbf{x}}_k^-) \quad (4)$$

$$P_K = P_k^- - K_k HP_k^- \quad (5)$$

(1) The current state is predicted from the previous moment state, plus external input.

(2) The forecasting process adds a new uncertainty Q, plus the previously existing uncertainty.

(3) The Kalman gain (weight) is calculated from the uncertainty P_k^- of the prediction result and the uncertainty R of the observation result.

(4) Perform a weighted average of the prediction results and the observation results to obtain a state estimate at the current time.

(5) Update P_K , which represents the uncertainty of the current state estimation.

III. EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

Measurement data Decorrelation: The site selected for the experiment is a rectangle of 14.2*18.8. The southwest corner of the room is used as the coordinate origin. The east direction is the x-axis forward direction, the north direction is the positive direction of the y-axis, and six wireless routers are deployed on the peripheral edge of the room. They are known as access points (APs). The SSIDs of the six APs are used to distinguish the signal strength received at the same location. The room is divided into 1*1 grids, and the signals are accepted on the computer. Software that samples RSS values at the vertices of each mesh, a total of 252 sample points, each sample point lasts for 3 minutes, and then average the RSS of each AP during this period as the signal strength value of the AP at the sample point. The deployment of the experimental environment is as shown:

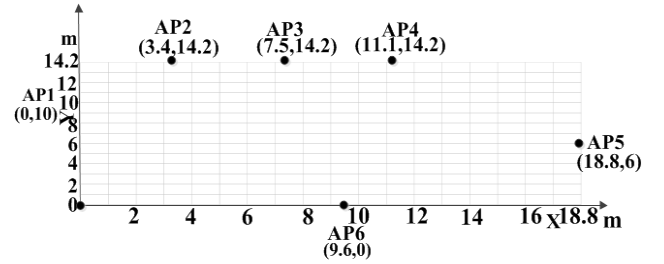


Fig.4. Experimental environment deployment diagram

The experiment is based on the Wi-Fi analyzer developed by the Android platform to collect the signal strength in the test area, and the fingerprint database is created by SQL-Serve 2008.

The matching algorithms mainly used in the online stage include classical k-nearest neighbor algorithm, svm, linear regression, gradient lifting, random forest, and neural network multi-layer perceptron. A variety of machine learning classification algorithms were calculated and tested in the python environment. The results of the experiment are as follows table 1.

It can be seen from the final positioning accuracy that the K-nearest neighbor algorithm has the best positioning accuracy, while the logistic regression has the worst positioning accuracy. The random forest, SVM, gradient lifting algorithm and neural network multi-layer perceptron positioning accuracy are not much different, the whole positioning The accuracy range is around 2~3 meters.

TABLE I. MACHINE LEARNING POSITIONING ACCURACY COMPARISON

algorithm	positioning accuracy
KNN	2.21m
logistic regression	3.09m
Support vector machine	2.25m
random forest	2.24m
Gradient Boosting for regression	2.22m
Multi-layer Perceptron regressor	2.45m

Through the comparison of the above results, it is found that the selection of different machine learning algorithm models can not effectively improve the positioning accuracy. Based on the above analysis, this paper proposes a method

of combining the machine learning model and the target tracking algorithm to improve the positioning accuracy. In the final positioning, first obtain a position estimate (observation position) by position fingerprinting method (assuming that the moving target is uniform motion), the current position (predicted position) can be predicted from the position and velocity of the previous moment, and then The observation results and the predicted results are weighted averaged as the final positioning result. Position fingerprinting The knn positioning results are subjected to Kalman filtering and particle filtering, respectively, and the results are shown in the figure.

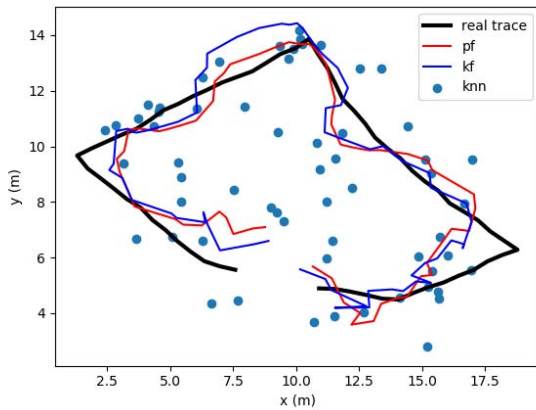


Fig.5.Track comparison

By using KF and PF filtering, it can be seen from the figure that the positioning accuracy is improved from 2.12m to 1.7m, as shown in the following table. Compared with the fingerprint localization result of the classical K-nearest neighbor algorithm in [6], the positioning accuracy is improved by 20%. It is concluded that the target tracking algorithm can effectively improve the positioning accuracy of machine learning algorithms such as knn.

TABLE II. KALMAN AND GRANULAR FILTER SUB-POSITIONING

algorithm	accuracy
KNN	2.21521479398 m
KNN+Kalman Filter	1.77116239607 m

KNN+Particle Filter	1.79881825483 m
---------------------	-----------------

IV. CONCLUSION

In this paper, by comparing various indoor positioning methods, the fingerprint localization technology based on RSS is given, and several classification algorithms are compared with experimental data. It can be seen from the analysis of experimental results that the positioning accuracy of various classification algorithms is not much different. How to improve the positioning accuracy on the existing basis is the focus of this paper. Based on the KNN localization algorithm, the target tracking algorithm is used to process the localization result of KNN location fingerprint localization algorithm. The experimental results show that this method can effectively improve the positioning accuracy.

REFERENCES

- [1] Youssef, Moustafa. "The Horus WLAN location determination system." *Proc. International Conference on Mobile Systems, Applications, and Services* 2005:357-374.
- [2] Chen Lina WLAN based location fingerprint indoor positioning technology [M] Beijing: Science Press, 2015.
- [3] Zhang Minghua, Zhang Shensheng, Cao Jian, Indoor Positioning Based on Signal Strength in Wireless LAN[J]. *Computer Science*, 2007 (6): 68-71.
- [4] Bahl P, Padmanabhan V N. RADAR: an In-Building RF-based user location and tracking system[C]. *Tel Aviv: Nineteenth Joint Conference of the IEEE Computer and Communications Societies*, IEEE Xplore, 2000:775-784 vol.2.
- [5] Moustafay, Ashoka. The horus, location determination system [J]. *Wireless Networks*, 2008 (3) : 357-374.
- [6] Zhang Yuwen, Wang Yunjia, Wang Xingfeng. Application of Affine Propagation Clustering in Indoor Positioning Fingerprint Database[J]. *Bulletin of Surveying and Mapping*, 2014 (12): 36-39.
- [7] Tang Xiaomou, Tang Jiajie An indoor positioning algorithm based on probability distribution propagation clustering[J]. *Telecommunications Engineering Technology and Standardization*, 2013(8): 62-67.
- [8] Frey, Brendan J, Delbert D. Clustering by passing messages between data points[J]. *Science*, 2007 (5814) : 972-976.
- [9] S. Sen, R. Choudhury, S. Nelakuditi. Spin Loc: spin once to know your location[C]. *Twelfth Workshop on Mobile Computing Systems & Applications*, ACM, San Diego, USA, 2012, 1-6.
- [10] M. Kotaru, K. Joshi, D. Bharadia, et al. Spot Fi: Decimeter Level Localization Using Wi-Fi[J]. *ACM SIGCOMM Computer Communication Review*, 2015, 45(5):269-2.