Research on Location Fingerprint Towards Three-dimensional Indoor Positioning System

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***Abstract*—This paper proposed a solution to three-dimensional indoor positioning system based on location fingerprint method. Especially, this paper proposed a automatic offline collection method and realizes a off-line collection system, including a collection server and a mobile collection applications, which can be used to collection the information of location fingerprint conveniently, and also improve the efficiency of the off line collection. Moreover, this paper studied the three-dimensional positioning system based on the location fingerprint method, which can obtain the indoor location information with a relative high accuracy. In addition, the authors improve the algorithm based on the location fingerprint, which improves the positioning accuracy and optimizes the positioning performance.**

Keywords—indoor positioning; location fingerprint; three-dimensional; NNSS-AVG; RSS

I. INTRODUCTION

With the development of wireless network and mobile technology, people tend to use location based service to get access to location information. Location information service has been brought into many fields such as big data, cloud computing, Internet of things, O2O and other new technologies and new applications[1-3].

WLAN positioning technology includes Received Signal Strength (RSS)[4], Angle of Arrival (AOA) [5] and Time of Arrival (TOA) [6]. The special hardware equipment is required in AOA and TOA positioning technology, which is used for precise measurement and synchronization of angle and time. Compared with AOA and TOA, the RSS does not require additional special equipment and has the following advantages:

(1) Fully based on the existing network infrastructure and mobile terminals, no additional equipment is required;

(2) High positioning accuracy within several meters;

(3) The positioning delay is very small, and does not need to search the satellite at the first time.

The RSS still can be divided into two kinds of positioning technologies: location fingerprint method and communication model method. These two methods are different in the way that the RSS value of the wireless signal combined with the position information. Because the accuracy of the communication model method is lower and the adaptability to the environment is poorer, the location fingerprint method in the indoor positioning technology is generally preferred. The positioning technology based on location fingerprint can provide less delay of indoor positioning and higher precision.

However, the location fingerprint technology is not mature, and there is no large-scale commercial use in the market. The most important reason is that the location fingerprint technology is required to collect the location fingerprint information, and the work is time-consuming compared with the benefit. Furthermore, the two-dimensional spatial positioning cannot meet the needs of location services in many cases and the height of the object and the personnel information is becoming more important. For example, in the event of a fire alarm and other disasters, we need to determine the height, which will impact the rescue effect.

In addition, LBS have been widely used in some areas such as public security and cultural exhibition. In an exhibition or a shopping mall, the display may also be placed in different height. Although the height information is so important, there is still no one successfully carrying on the three-dimensional space positioning research using location fingerprint technology, which is because the three-dimensional space of the offline fingerprint collection is more than two-dimensional space.

In this paper, we present a new type of deterministic algorithm named NNSS-AP-AVG based on the NNSS-AVG algorithm, which has better performance on the indoor positioning technology based on the location fingerprint method, especially for three-dimensions.

Moreover, our research of this paper has the following advantages:

(1) An NNSS-AP-AVG location fingerprint algorithm is proposed, which is based on an adjustable parameter of Nearest Neighbor(s) in Signal Space method. The NNSS-AP-AVG method is an improved algorithm based on the NNSS-AVG, which aims to avoid the parameter K fixed in signal space. If parameter K in nearest neighbor method is fixed, the similarity will not enough to participate the calculation in the location fingerprint, which will result in accuracy decrease.

(2) The 3D positioning system based on the location fingerprint system is realized, which including the positioning server and the positioning mobile application. The positioning server is developed on Java EE, in which deployment the NNSS-AP-AVG positioning algorithm. The positioning mobile application is developed on Android, and can display the 3D location of the users. The positioning accuracy of 3D indoor positioning system can satisfy the majority of the 3D position needs.

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(3) An automatic offline collection system is implemented, which includes the collection server and collection mobile application. In the offline acquisition phase, the use of automatic offline collection system can effectively collection the location of fingerprint and reduce the workload of the offline collection.

(4) The influencing factors of the location fingerprint method is studied, which are useful to improve the positioning accuracy and can be the references in arranging the location fingerprint system in the future.

II. SYSTEM ARCHITECTURE

The principle of location fingerprint method is that the characteristics of the RSS signal received in different physical locations are unique and distinguishable. According to this feature, we can construct a database, which is used to map the physical location to the received RSS signal characteristics. When we know the characteristics of the received RSS signal, we can also get the physical location of the RSS signal.

Indoor positioning based on location fingerprint consists of two stages: offline collection stage and online positioning stage. The main purpose of the offline collection stage is to build the location fingerprint database and the main purpose of online positioning stage is to estimate the location of the target in the test environment.

The database of fingerprint locations will be set up in the offline acquisition phase, which relating the position information and the RSS vectors. The RSS vector consists of signal intensity received by all Aps, which we call it the location fingerprint. In the offline acquisition phase, the user first selects a number of reference points in the environment to be tested, and then recorded the entire wireless signal intensities of reference points received by Aps. When all the positions of the fingerprints stored in the database, the construction of the location fingerprint database is completed.

The location will be estimated in the online positioning stage, where the user estimated the position using the signal intensity received from each Aps. The location fingerprint algorithm is calculated to estimate the position to be measured. The position can be measured both in the three-dimensional space and two-dimensional space. In this paper, the position of the location fingerprint means the space coordinates. The diagram of fingerprint positioning workflow is shown in Fig. 1.

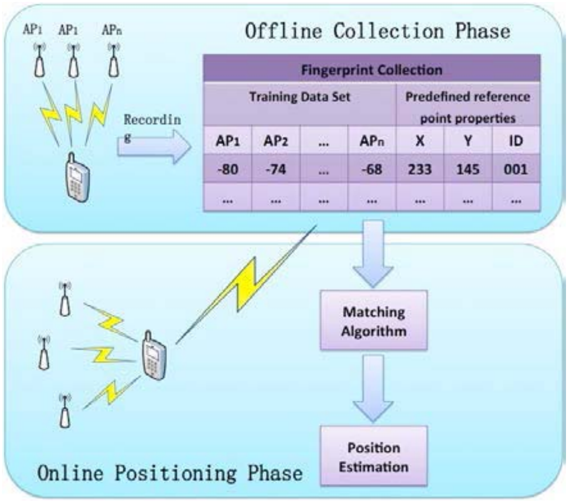

Fig. 1. The diagram of fingerprint positioning workflow

A. NNSS

The Nearest Neighbor(s) in Signal Space (NNSS) is the most classical deterministic positioning algorithm, which is proposed by RADAR system.

The location fingerprint positioning system is based on the NNSS algorithm, which will be calculated by the following Euclidean distance equation

$$Euclidean\ distance = \sqrt{\sum_{i=1}^{n}(F^i - S^i)^2} \qquad (1)$$

Where the parameter F is location fingerprint data measured in the online position stage and parameter S is the location fingerprint data settled from the location fingerprint database in the offline acquisition phase.

The location of the fingerprint data is determined as the minimum of the Euclidean distance. This paper presents an improved algorithm named NNSS Adjustable Parameter Average (NNSS-AVG) based on NNSS.

B. NNSS-AVG

The algorithm of NNSS-AVG, which is also designed by the developers of RADAR system, is applied to the RADAR-2 system. The NNSS-AVG is calculated as the mean of the first kn minimum of the Euclidean distance, which determined from the location fingerprint data measured in the online position stage and location fingerprint data settled from the location fingerprint database in the offline acquisition phase. The workflow of the NNSS-AVG algorithm is shown in Fig.2.

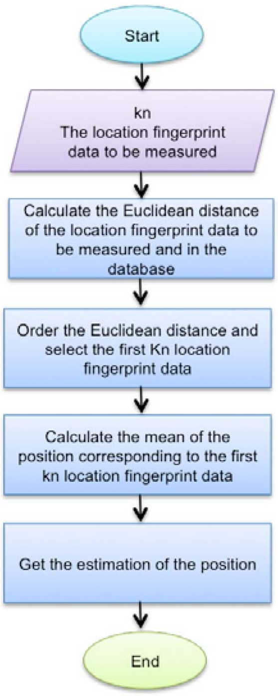

Fig. 2. The workflow of the NNSS-AVG algorithm

C. *NNSS-AP-AVG*

The algorithm of NNSS-AP-AVG is improved from NNSS-AVG and can be implemented as the following steps:

- Calculate and order the Euclidean distance of the location fingerprint data to be measured and the location fingerprint data in the database;
- Select Q location fingerprint data that less than M times the minimum Euclidean distance;
- Compared Q with kn of the initial input, and select the the smaller one as P;
- Calculated the weighted average of the P location fingerprint data with smaller Euclidean distance, where the weighted average parameters are the normalized Euclidean distance.

There are two main improvements of NNSS-AP-AVG compared with NNSS-AVG:

- The fixed kn is modified to a small number between kn and Q, which is called P, and the Q is the number of location fingerprints where the Euclidean distance is less than M times the minimum Euclidean distance.
- The estimate average is modified as a weighted average.

The first point of the improvement is that we try to prevent the kn fixation caused by the non-similar locations to participate in the estimation, which is because if the number of the estimated locations is fixed, and if not enough number of the similar locations join in the calculation, there will result in a larger estimation error. Secondly, the purpose of the comparison between kn and Q is to prevent the Q value to become too large which will involve too much locations to participate in the estimate. If the Q value is too large, then the estimated location will not be similar. Thus, we use the threshold of kn to limit the number of participants in the estimates.

The second point of the improvement is that we try to increase the weight of the similar location fingerprints, that is, the estimated location is more close to the location of the fingerprint, which is more accurate. The weighted NNSS-AVG algorithm also uses this method.

The workflow of NNSS-AP-AVG algorithm can be shown as the following diagram, see Fig. 3.

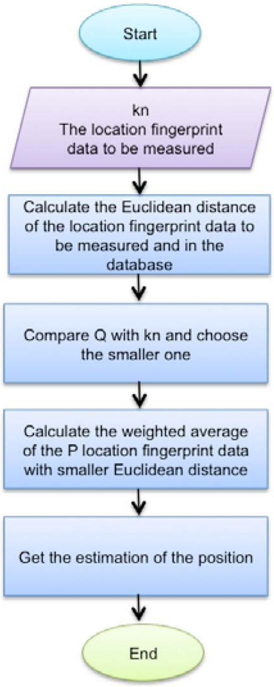

Fig. 3. The workflow of NNSS-AP-AVG algorithm

III. System Solution

A. *Clustering Analysis*

In the location fingerprint method, we need to search and compare for the location fingerprints data among the whole fingerprint database, which is a large and complex computation. In order to reduce the computation complexity, we introduce a clustering method in the location fingerprint method.

Clustering analysis is a multivariate statistical method used in pattern recognition, machine learning, data mining, image processing, etc. Clustering analysis can be divided into hierarchical clustering and non-hierarchical clustering. For hierarchical clustering, the key is to define the class distance. For non-hierarchical clustering, which is referred to a kind of clustering methods, the common feature is to give an immature initial classification, and revise it repeatedly according to some certain rules, until the classification become reasonable. Compared with hierarchical clustering, the non-hierarchical clustering method has better classification accuracy, and occupies less system resources. In this paper, we choose the classical K-means method in non-hierarchical clustering method. The clustering algorithm flow chart is shown below in Fig.4.

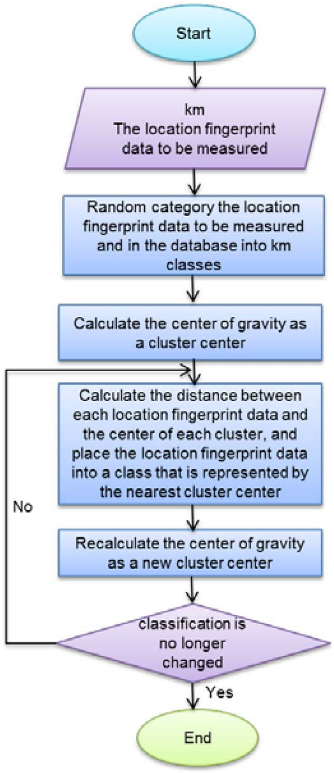

Fig. 4. The clustering algorithm flow chart

Flow chart steps are shown as follows:

- Set km which is the number of clusters;
- Random category the fingerprint data to be measured and the location fingerprint data in the database into km classes.
- Calculate the center of gravity as a cluster center;
- Calculate the distance between each location fingerprint data and the center of each cluster, and place the location fingerprint data into a class that is represented by the nearest cluster center. Recalculate the center of gravity as a new cluster center;
- Repeat last step until the resulting classification is no longer changed.

B. 3D NNSS-AP-AVG Positioning Algorithm

In order to realize the 3D positioning system based on location fingerprint, we choose a three-dimensional space of 12 meters long, 1.6 meters wide and 2 meters high as an experiment environment, as shown in Fig. 5.

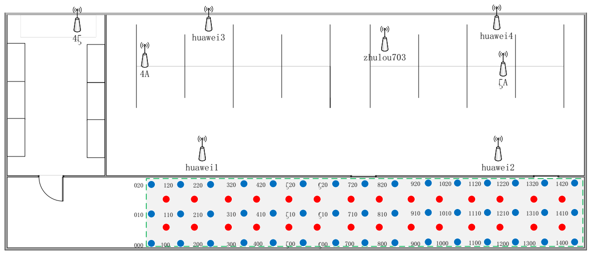

Fig. 5. The layout of reference points in the 3D testing environment

We choose the reference points in every 0.8 meters, which is highlighted in the color blue. And the height of the reference points was selected as 0.4 meters, 1.2 meters, 2 meters, respectively. We use our own automatic acquisition application named CUCFC instead of inSSIDer to collect the location fingerprint data. We use CUCFC to collect 30 location fingerprint data at each reference point. We set up the position to be measured at each reference point of 1.2 meters high, and a total of 28 to be measured with the red color. We also have used CUCFC to collect the 30 position and record the position information.

We use NNSS-AP-AVG to implement the MATLAB algorithm. By adjusting the parameters of kn and Q, the 3D positioning accuracy can be achieved by NNSS-AP-AVG algorithm.

In detail, we calculate the Euclidean distance between the position of 28 points to be measured and the position of the 135 reference points. Then we get the estimated position according to the NNSS-AP-AVG algorithm, and get the 3D coordinates. The Euclidean distance are calculated between the coordinates of 28 points to be measured and their real coordinates, then the estimation errors are calculated and the CDF and ARMSE are calculated.

First, we do the simulation with different kn values when M value is fixed. When M value is fixed at 3.75, and the kn is taken as 15, 30, 45, 90, 135, respectively, the results are shown in Fig.6. When kn equals to 45, as shown in the figure, the CDF reaches the highest value, which means the highest positioning accuracy. When kn equals to 90 or 135, the CDF is higher within a certain range of 0.5 meter. This is because when kn takes a larger value, according to the NNSS-AP-AVG algorithm, M value will take the main role, and will let all the position with similar conditions to involved in the estimation, which may result in a high accuracy in a certain range. But in a larger range of estimation, we need to determine the threshold of kn by simulation. In this paper, kn equals to 45 in the three-dimensional experimental environment.

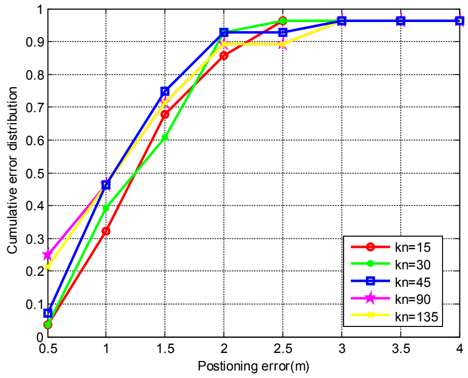

Fig. 6. The results of NNSS-AP-AVG algorithm with different kn

Then we determine the threshold of kn equals to 45, and do the simulation with different M to test if the positioning accuracy changes. The M values are taken as 1, 1.5, 2.25, 3, 3.75, 4.5, respectively, and the results are shown in Fig.7. When M equals to 3.75, the CDF reaches the highest value, which means the highest accuracy can be reached at of CDF equals to 96.43% within 3 meters. In the case of M equals to 1, the NNSS-AP-AVG algorithm becomes the NNSS algorithm, and the positioning accuracy is significantly lower than the NNSS-AP-AVG algorithm. When M is less than 3.75, the CDF is increased when M value is increasing. This indicates that more positions involves in the estimation can improve the position accuracy when M value is less than 3.75. Therefore, in this paper, M value is taken as 3.75 in the three-dimensional space experiment environment.

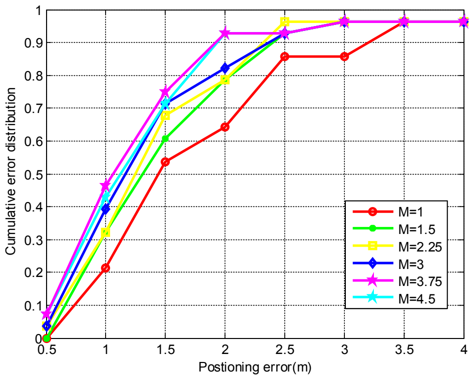

Fig. 7. The results of NNSS-AP-AVG algorithm with different M

In the research of NNSS-AP-AVG algorithm, we also do the simulation with clustering analysis. We still use the K-means algorithm to replace the location fingerprint database of 135 location fingerprint data with cluster. We take kn equals to 45 and M equals to 3.75, respectively, the km is taken from 1 to 6, and the simulation results are shown in Fig.8. When km equals to 1 with no clustering, the CDF reaches the highest, which means the positioning accuracy is the highest. When km does not equal to 1, the highest CDF can be obtained when km equals to 3, which means the highest positioning accuracy with clustering.

The simulation results show that the clustering analysis can improve the accuracy of the location fingerprint estimation, because the clustering analysis can reduce the calculation time of the Euclidean distance by replace the location fingerprint database with a cluster. Therefore, in the 3D experimental environment, we use NNSS-AP-AVG algorithm with clustering analysis. Its positioning accuracy can reach when CDF is 96.43% within 3 meters' range.

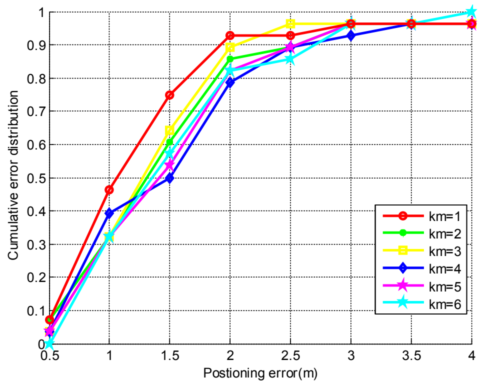

Fig. 8. The results of 3D positioning algorithm with different km

IV. CONCLUSIONS

This paper introduces a 3D indoor positioning system using location fingerprint method. Especially, in order to achieve the highest positioning accuracy, we use a novel-positioning algorithm named NNSS-AP-AVG based on NNSS-AVG (Nearest Neighbor(s) in Signal Space-Average) in the location fingerprint method. Moreover, in order to improve the positioning accuracy, we introduce the clustering analysis to reduce the calculation time of the Euclidean distance by replace the location fingerprint database with a cluster. In addition, to solve the hard work of offline phase, a fingerprint collecting system is implemented. The simulation results demonstrated that the 3D indoor positioning system can achieve higher positioning accuracy when we use NNSS-AP-AVG algorithm with clustering analysis.

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