Modified Fingerprinting Algorithm for Indoor Location

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Abstract —This paper proposes a modified fingerprinting hybrid location algorithm for homogeneous and heterogeneous indoor environment. The new method is designed based on fingerprinting to improve the location accuracy. It works in two phases: one is offline phase, which opts for the location of reference point by different kind of complex regions. Another one is online phase, which proposes dynamic K for finding the nearest reference point to improve location accuracy. Sensor-assisted tracking hybrid positioning function is utilized to further improve the low location accuracy problem of heterogeneous regions. Simulation results show that the new method obtains approximately 37.7% improvement comparing with the classical fingerprinting-based algorithms, the location accuracy reaches to 0.5m in 200m×200m heterogeneous network.

Index Terms—Fingerprinting algorithm, indoor location, dynamic k, sensor-assisted tracking

I. Introduction

Location Based Services (LBS) have been flourished with the rapid developments in network technology and portable mobile sensing devices. LBS have played an important role in dealing with public emergencies, widely applied in school, hospital, library, warehouse, etc., especially the applications for indoor location [1], [2]. Literature [3] proposed a kind of geographical fingerprint by artificial neural network to reduce handoff delay of wireless access in vehicular environments. An effective indoor localization method of hybrid RSSI/TDOA is improved to settle the big errors occurred during indoor RSSI localization and high cost paid by TDOA localization [4]. Space Annotator which is a high precision location system is provided for asset management. It works well even in managing small volume [5]. Therefore, high precision location algorithm is the crux to obtain the location information of these scenarios. Recently, many location algorithms have been introduced, such as A-GPS [6], Ultra-Wide-Band (UWB) systems [7], [8], Time Difference of Arrival (TDOA) [9], [10], Angle of Arrival (AOA) [11] and RSSI-based models [12], etc. Fingerprinting location algorithm is becoming a research focus in indoor location for its well-done location performance and high location accuracy [13], [14].

Fingerprinting location algorithm is a location method which utilizes Received Signal Strength Indication (RSSI) of Wireless Local Area Networks (WLAN) [15]. Different indoor layout, material structure and indoor equipment scale lead to large signal path loss and inaccurate received signal strength value, so the location accuracy is reduced. In order to solve these problems, in [16], a method of filtering interference for RSSI has been proposed. However, it merely can be applied to the uniform environment since the complexity of the environment is not considered. Hybrid WLAN-RFID indoor localization solution utilizing textile tag has been proposed in [17], which improves the location accuracy comparing with RFID or WLAN of individual work, but its structure is complicated and it spends long time on locating.

To overcome these deficiencies, a modified fingerprinting indoor hybrid positioning algorithm homogeneous and heterogeneous indoor environment is introduced in this paper. We divides larger location area into several same small areas, the uniformity of the network is judged by the RSSI of the points in each small area. Corresponding number of Reference Points (RPs) and Access Points (APs) are set in these small areas. Dynamic K is proposed to find the nearest reference points to locate. Sensor-assisted tracking [18]-[20] method is used to improve the location accuracy and not increased the amount of calculation in high complex environments.

The rest of this paper is organized as follows. Section II describes the fundamental and defect of the fingerprinting location. Section III presents the new method approach. Some simulation results are discussed in Section IV. Conclusions are stated in Section V.

II. Fingerprinting Location

Fingerprinting location mainly relies on the database of target feature to identify the position [21], it is similar to the fingerprint identification. The process is divided into two stages: offline (A) and online (B). Fig. 1 shows the process.

The fingerprint database is established in offline stage [22]. A range of known points, Reference Points (RPs) and Access Points (APs) are set in the location area. The form of location APs are represented as AP1, AP2, etc. RPs can be detected in the range of APs. The received signal strength (RSSIm) and location information of RPs

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(Xn, Yn) are measured. The data of information is processed and stored in the fingerprint database.

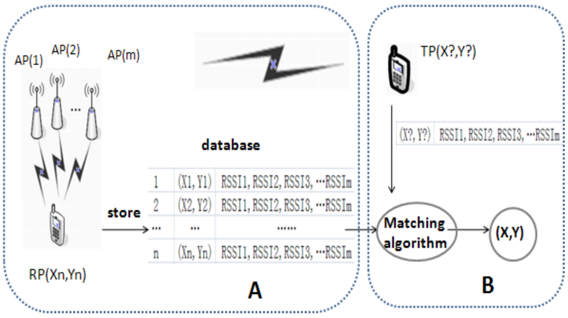


Fig. 1. Location fingerprinting positioning.

The received signal strength of Test Points (TPs) are compared with the data of fingerprint database in terms of corresponding matching algorithms in online stage. The estimated position is calculated. These algorithms include Neural Networks [23], Nearest Neighbour (NN) [24], K-nearest (KNN) [25], etc. KNN is adopted for the reason that it has a higher positioning accuracy. Nearest Neighbour KNN is a deterministic positioning algorithm to find the closest RPs to the TPs. A threshold such as -60dBm is set to determine which AP works. The real value of RSSI is compared with the fingerprint database, and the Euclidean distance of received signal strength between TPs and RPs is calculated from (1), (2) [1].

$$d_m = \sqrt{\begin{array}{l}(RSSIT_m - RSSIR_{ji}{}^2 + (RSSIT_m - RSSIR_{j2})^2 \\ +\ldots + (RSSIT_m - RSSIR_{ji})^2\end{array}} \quad (1)$$

$$(\bar{x}, \bar{y}) = \frac{1}{K}\sum_{k=1}^{K}(x_k, y_k) \quad (2)$$

where j is the number of RPs in database, $j \geq 1$, i represents the number of located APs for each small area, $i \geq 1$, m is the number of TPs, $m \geq 1$, K stands for the closest RPs, ($RSSIR_{j1}, RSSIR_{j2}, \ldots RSSIR_{ji}$) is the received signal strength of RPs, $RSSIT_m$ is the signal strength of TP, (x_k, y_k) is the *K-th* position information of the fingerprint in (2).

Fingerprinting location algorithm has high location accuracy in ideal environment. However, significant errors and generous calculation may happen during the RSSI acquisition due to the serious of the surrounding environment. Therefore, this method is suitable for the simple environment with fewer obstacles.

III. Modified Fingerprinting of Hybrid Indoor Location Algorithm

A new positioning algorithm is proposed to improve the location accuracy and reduce the algorithm calculation in homogeneous and heterogeneous.

We simulate one real environment, RPs are arranged randomly. RSSI of RPs is small before offline phase. The distribution of points is concentrated in the homogeneous area and scattered in the heterogeneous area. To reduce the redundancy of fingerprint database, the location area is divided into several sub-areas in the same size and the RSSI is clustered. Fig. 2 shows the arrangement of RPs and APs. There is more obstacles and distractions in the heterogeneous area, homogeneous area is fewer obstacles and the RSSI of RPs is greater than the homogeneous area in the same distance. APs are arranged at the top of every small area in the light of the signal transmission characteristics and RPs are arranged in the homogeneous and heterogeneous environment.

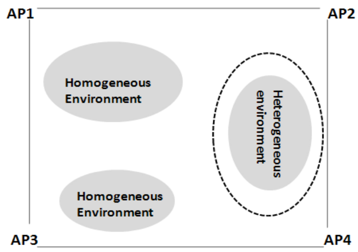


Fig. 2. Profile of environment

The lognormal shadowing model is given by [3], [16]:

$$P_{L(d)} = P_{L(d_0)} - 10n\lg(d/d_0) + x_\delta \quad (3)$$

where $P_{L(d)}$ is the received signal strength; $P_{L(d_0)}$ is the RSSI at the reference distance d_0, n is the environment attenuation coefficient(0-7), x_δ is a zero-mean Gaussian random variable with a standard deviation *σ*. We use simulation parameters of the lognormal shadowing model in Table I. These parameters have been acquired from many experiments.

TABLE I: VALUES OF LOGNORMAL SHADOWING MODEL

Parameters	Values
d_0	1m
n	2.31
$P_{L(d_0)}$	-45dBm
x_δ	0-7

Receiving signal is unstable for various environmental factors, RSSI needs to be pre-processing before the online positioning. The probability of the data for continuous value is processed and the singular point is filtered by setting a probability threshold, it is -60dbm in this paper. Then the average value of the RSSI for high probability is processed and stored in the database as a reference value.

Signal strength is affected strongly by the adjacent RPs, so the RSSI Euclidean distance method is used to find the nearest RPs in online matching stage. We select dynamic K value method instead of the KNN to find out the nearest RPs in each small area. A threshold value of Euclidean distance is set from 2.1 to 5.5 in the simulation to reduce the complexity of calculation and the positioning time. The value of K is set from 1 to 8. In the heterogeneous region, the sensor-assisted tracking method is constituted by magnetometer and other sensors.

Smart phones and other mobile terminals are equipped with magnetometers and other sensors to determine the direction of TPs and the number of steps. The length of the TPs' stride is determined by the length of the TPs. The position of TPs is estimated by the historical location information. The model for heterogeneous regional position is defined in the Atos-SensorSim simulation platform. The expression position is given by:

$$\begin{cases} x_{k+1} = x_k + ks.\cos\theta \\ y_{k+1} = y_k + ks.\sin\theta \end{cases} \tag{4}$$

where k is the number of TPs' step, s is the length of step, θ is the direction of TP. The sensors are devoted to measure the parameters. Table II details the parameters of the simulation.

TABLE II: DATA RANGE OF SIMULATION PARAMETERS

Parameters	Values
s	0.5m
k	N^+
θ	0 °-90 °

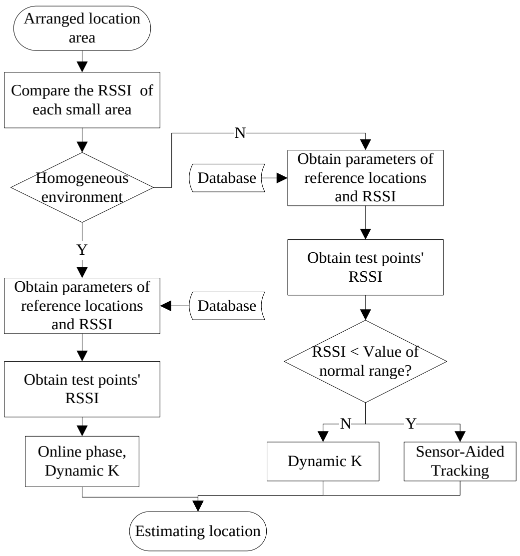


Fig. 3. Flowchart of modified fingerprinting indoor hybrid positioning

Positioning time increases significantly after the sensor-assisted location method is added, so the sensor-assisted location method is well-performed in the heterogeneous area. Fig. 3 shows the process of modified fingerprinting indoor hybrid location algorithm for homogeneous and heterogeneous indoor environment.

The quantity of APs and RPs are randomly arranged in location area according to the size of the area. Signal strength is measured to establish a fingerprint database. To reduce the time of online comparison, TPs is first determined to which sub-area it belongs. The dynamic K is used to find the nearest RPs to estimate its position. When the RSSI is lower than the value of normal range, sensor-aided tracking method is adopted to ensure the positioning accuracy in heterogeneous area.

IV. SIMULATION RESULTS

In this section, we provide some simulation results of modified fingerprinting method for indoor location proposed in this paper. A novel sensor network simulator Atos-SensorSim is used 1200 nodes and 90 APs are set in the network environment of 200m×200m. The uniformity of the network is judged by the RSSI of the points. Fig. 4 shows the simulation environment.

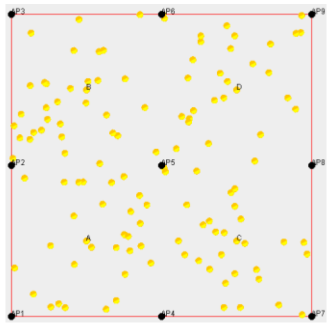
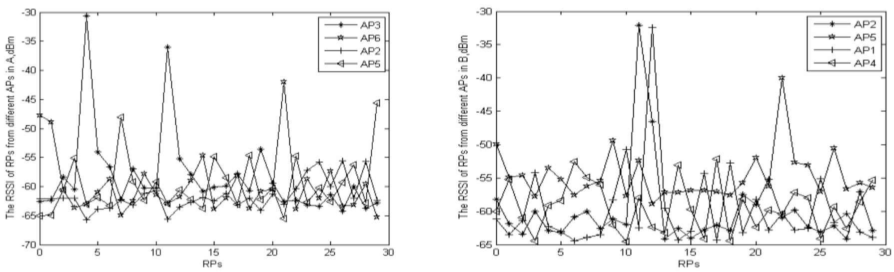


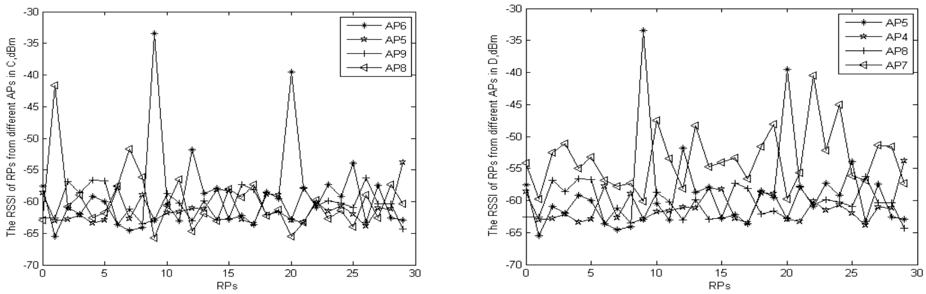
Fig. 4. The environment of the simulation.

Fingerprinting orientation is decided by the received signal strength. The RSSI is crux for positioning. Fig. 5 shows the RSSI of RPs in homogeneous area. We selected 9 APs randomly. The lines represent the average RSS value in the four small areas. The range of fluctuation is small and RSSI is generally from -65 dBm to -50 dBm. This location area is set fewer obstacles. In the homogeneous area, RPs are distributed evenly. Fig. 6 shows the regional distribution result. The area is divided into 4 small areas. We randomly set 9 APs in the simulator and they are located at the top of every small area, then some TPs are tested in the location area. Dynamic K used is proposed to improve the location accuracy.



(a)

(b)



(c) (d)

Fig. 5. The RSSI of 200m×200m homogeneous network.

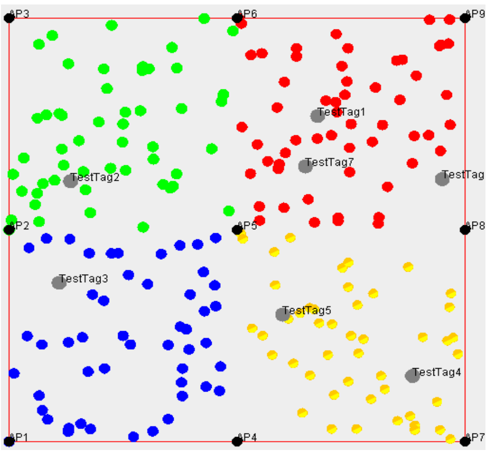


Fig. 6. Distribution of homogeneous network.

Fig. 7 shows the positioning result of 200m×200m homogeneous network. The classical fingerprinting-based algorithm and our new algorithm are compared in the same 4 APs. It is seen that the location accuracy of the classical fingerprinting-based algorithm is inaccurate, such as K=3, etc. Position accuracy is generally about 1 m. If dynamic K is applied, the error is 0.2 m. The new method improves the location accuracy significantly.

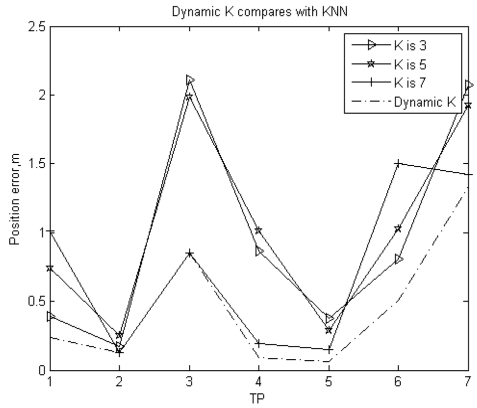
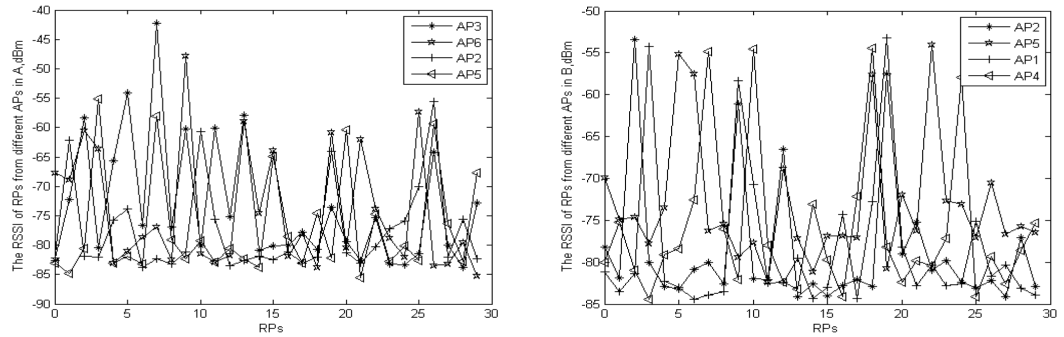
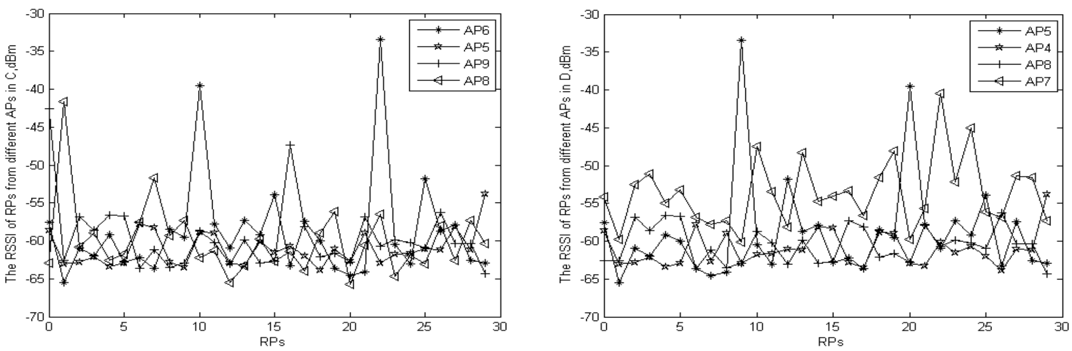


Fig. 7. 200m×200m homogeneous network positioning results



(a) (b)



(c) (d)

Fig. 8. The RSSI of 200m×200m heterogeneous network.

Fig. 8 shows the RSSI of 200m×200m heterogeneous network. The range of fluctuation is large and RSSI is generally from -85 dBm to -55dBm in Fig. 8a-b. The location area is set many obstacles. The range of RSSI is from -65dBm to –50dBm in Fig. 8c-d. The location area is set fewer obstacles. The reason for this kind of phenomenon is caused by the numerous obstacles in the heterogeneous area. Different indoor layout and obstacles lead to large signal path loss and inaccurate received signal strength value. They affect the location accuracy seriously.

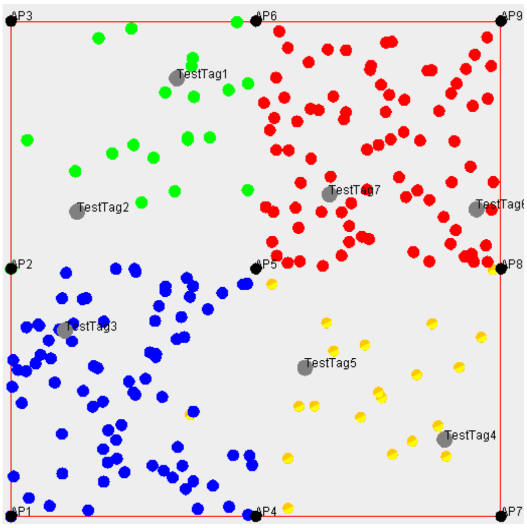
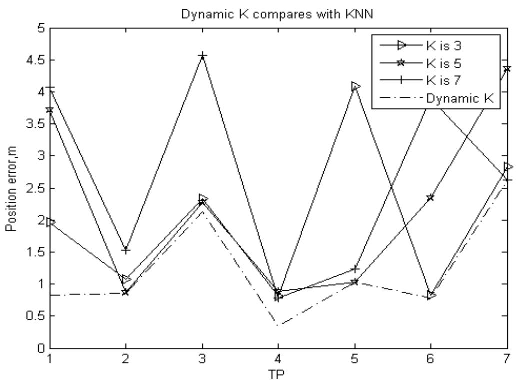
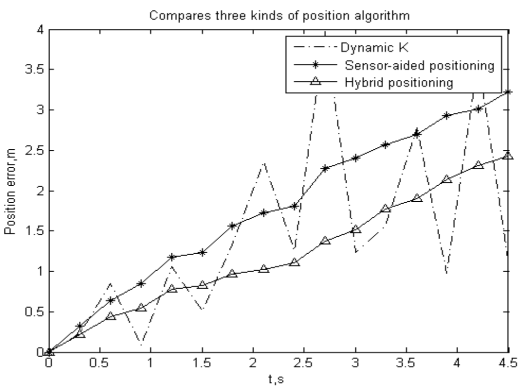


Fig. 9. Distribution of heterogeneous network



(a)



(b)

Fig. 10. The positioning results of 200m×200m heterogeneous network.

Fig. 9 shows the distribution of RPs and APs in the heterogeneous network. Green and yellow nodes are set in the two sparse areas, red and blue nodes are set in the two intensive areas. The distribution of points is concentrated in the homogeneous part and is scattered in the heterogeneous part. Dynamic K is proposed to improve the location accuracy. Sensor-assisted location method is added to the heterogeneous area, which is applied to track the trajectory of TPs.

Fig. 10 shows the positioning result of high heterogeneous environment in 200m×200m network. Fig. 10a shows the location accuracy of dynamic *K*. Fig. 10b shows sensor-assisted tracking method is added to solve the high complex environment. It is seen that the location accuracy of dynamic *K* is less than 1m compared to the greater than 4m of *K* =7. It is obvious that the dynamic *K* value increases location accuracy. However, part of areas is high complex, the positioning error is still higher even if the dynamic *K* value is involved. In this situation, the sensor-assisted tracking method is added to solve the problem. When TP is detected from complex partial region, sensor-assisted tracking method is adopted. Fig. 10(b) shows that the modified fingerprinting indoor hybrid location algorithm has the highest location accuracy and the location accuracy reaches to 0.5m in 200m×200m heterogeneous network.

V. Conclusions

Modified fingerprinting hybrid algorithm for indoor location has been proposed in this article. Reference points are chosen by different kinds of complex region in the offline stage and dynamic K is used to find the nearest RPs. In order to improve the location accuracy, sensor-assisted hybrid positioning method is added into heterogeneous environment. The scheme solves the problem of location homogeneous and heterogeneous areas, especially the high complex area of heterogeneous environment. The simulation results show that the method obtains approximately 37.7% improvement comparing with the classical fingerprinting-based algorithms, the position accuracy is around 0.5m in the heterogeneous network of 200m×200m. The algorithm idea can be applied to various application scenarios, such as school, hospital, library, warehouse, etc.

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