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A Reduced Location Area Algorithm for Indoor Localization Enhancement

Chunkai Chen[1], Baocong Liu[2]
[1](School of Electronics and Information Engineering, TianGong University, Tianjin)
[2](School of Electronics and Information Engineering, TianGong University, Tianjin)
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Abstract: WiFi fingerprint localization is widely used in indoor location. To solve the problem of signal fluctuation and the difference between signal space and physical space. This paper proposes a reduced localization area algorithm. Localization region is first dynamically selected, and then the location estimation is achieved by the soft range limited K-nearest neighbours (SRL-KNNs) algorithm. In first step, localization area is reduced by matching the ordered access points (AP) sequence to the ones in the fingerprint map. The second step is accomplished by utilizing the SRL-KNNs algorithm in the selected area. Experimental results show that compared to the traditional nearest neighbour method, the computational complexity is reduced, and the reduced localization area algorithm achieves an average localization error of 0.74 m with 75% of the error within 1m.
Key Word: Indoor location;WiFi fingerprint; Reduced location area; AP sequence; SRL-KNNs.

I. INTRODUCTION

Propagation model algorithm can be used for indoor positioning. Estimate the position by measuring the distance or angle information between the target and the reference node, such as triangulation model, circumferential positioning model, etc. The ranging method is based on Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Angle of Arrival (AOA)[1]. However, such schemes do not work well indoors due to the building occlusion and multipath effects[2]. WiFi fingerprint[3] is another positioning method with high positioning accuracy and feasibility, achieved by establishing a mapping relationship between location and signal strength, instead of measuring the distance or angle. Due to complex indoor environment, the wireless signal strength is highly susceptible to obstructions, exact propagation model is difficult to obtain. Therefore, fingerprint method is more suitable for WiFi positioning. The research in this paper is based on WiFi fingerprint.

At the present, RADAR[4] and Horus[5] are the classic positioning systems based on WiFi fingerprint, and the positioning accuracy is 2~5m. WiFi fingerprinting positioning method includes offline and online stages[6]. In the off-line phase, the received signal strength (RSS) is collected from different WiFi access points (APs) at reference points (RPs) of known locations. Each reference point is represented by its unique WiFi signal vector, i.e. location fingerprint. These fingerprints are stored as part of the fingerprint database. In the online phase, the real-time WiFi signal is received through the mobile device from unknown location, and compared with the stored fingerprints utilizing the similarity metric in the signal space. The unknown location is then estimated based on the locations of the RPs whose fingerprints with the highest similarity to its RSS[7].

In the offline phase, it is necessary to get a large number of offline RPs to improve location accuracy, which requires time-consuming and laborious site survey. Some methods establish fingerprint database by extracting data characteristics of RSS. Based on machine learning, a support vector regression (SVR) method[8] is proposed to estimate the received signal strength of off-site survey locations in the environment. Some methods establish fingerprint database based on the idea of crowd sensing[9, 10]. Different from the mentioned two methods, proposed an AP sequence-based localization method, using the more stable differences of RSS between pairs of APs, instead of using the individual RSS readings[11]. Considering a signal sequence is more robust to noise than only the one RSS in the sequence. Although the average positioning accuracy is not ideal, this method greatly solved the problem of high consumption and signal fluctuation[12]. Therefore, this paper utilizes the method based on AP sequence to establish fingerprint database.

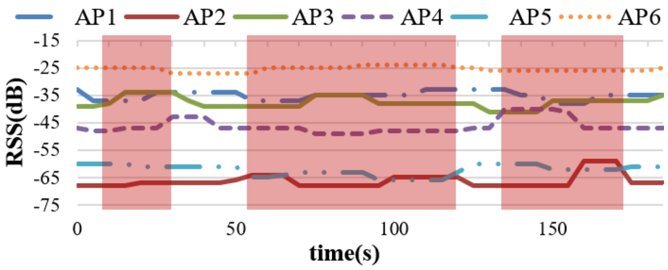
In the online phase, the match algorithms can be realized by deterministic and probabilistic methods. The deterministic methods use a similarity metric to match measured signals with fingerprint data in the database. The user's position is estimated as the nearest fingerprint position in the signal space. The most common similarity metric is the Euclidean distance between the online and offline fingerprint[13, 14]. The distance minimum positioning can be easily implemented based on k nearest neighbours (KNN)[15] and weighted k nearest neighbours (WKNN) [16]. The probabilistic methods estimate the target's location with the maximum probability distribution, such as Gaussian distribution and Bayesian criteria[17]. The position of the target is continuous, so the probability method is used to estimate the position of the target in the tracking system. If the system dynamic equation and the measurement equation are linear Gaussian, the Kalman filter algorithm is the optimal filtering algorithm, which can obtain the minimum mean square error estimate[18]. However, the state of the system tracking the moving target is usually nonlinear and non-Gaussian in practice. Inspired by these algorithms, Minh Tu et alpropose a soft range limited K-nearest neighbours (SRL-KNNs) localization fingerprinting algorithm[19]. It is based on KNN algorithm, it not only has low computational, estimated trajectory of the target is also more accurate due to the prior position is added to the calculation of Euclidean distance and therefore formed the soft range limit factor.

II. MATERIAL AND METHODS

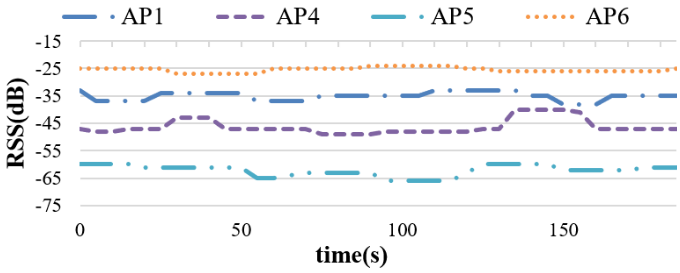
Based on the analysis of these fingerprint construction methods and indoor location methods, this paper proposes an algorithm to reduce the location area. In the offline phase, the fingerprint database is constructed using stable AP sequence. In the online stage, reduce the area by matching the ordered AP-sequence to the ones in the fingerprint map, which further reduces the calculation when utilizing the SRL-KNNs algorithm. The effectiveness of the algorithm was verified by experiments.

A.The RSS of WiFi

WiFi fingerprint localization estimate the location mainly relies on the similarity analysis between the collected RSS and the stored fingerprint. However,WiFi signals are susceptible to environmental interference as mentioned above. Different orientations, blocking and interference from devices can affect the RSS. But a lot of experiments have proved that the fluctuation range of RSS from stable APs does not exceed 10dB. Conventionally, the order of the RSS from different APs measured in the same location is more stable. Therefore, if the difference between adjacent RSS in the AP sequence does not exceed 10dB, the AP sequence is considered to have high reliability. As shown in Figure 1 (a), the RSS from 6 APs collected by a same device at a single point during a certain time. The marked red part is the AP sequence in a wrong order. The error distribution is caused by the similarity of RSS between AP1 and AP3, AP2 and AP5. Therefore, the APs should be selected first. As shown in Figure 1(b), AP2 and AP3 with similarities are removed, thus the RSS distribution is completely correct. After selection, the remaining APs will form an ordered AP sequence with high reliability.



(a)The RSS of all APs



(b) The RSS of selective APs

Figure 1. The signal strength distribution during three minutes of all APs and four APs at one test point.

B. Positioning algorithm

KNN is the most commonly used positioning algorithm due to its simple and effective. However, the similarity of signal strength is considered, regardless of the physical position. Some neighbours have high RSS similarity to their corresponding test points, while the physical location is far from it. As a result, such points will cause positioning error, as shown in Figure 2. Among the 7 neighbours of the test point that obtained according to the KNN algorithm (the number of neighbours in Figure 2 is based on the Euclidean distance to the test point RSS), the physical position of the 3rd and 7th neighbour is relatively far. If the weighted distance algorithm is used for positioning, the influence of the 7th neighbour will be reduced, but the third neighbour will lead to position error. Motivated by this, considering positioning a rough actual physical range, instead of traversing all RPs, the nearest neighbour method preformed within the range. In this way, the positioning area is determined based on the actual location and could solve the above mentioned problems. Furthermore, this method can also reduce the amount of calculation.

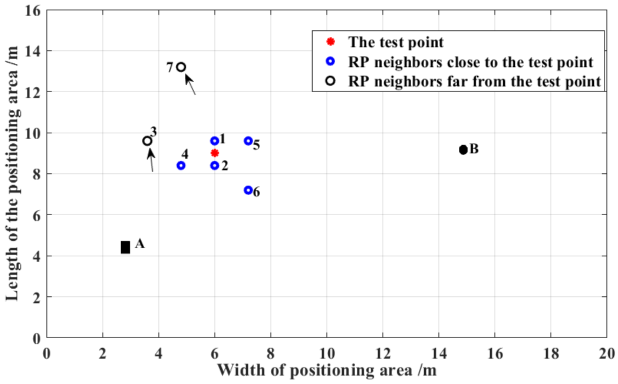


Figure 2.The physical location of the test points and RPs in the location scene.

In the reduced area, position estimation is accomplished by SRL-KNNs. The algorithm is based on KNN algorithm that the current position is related to the last estimated position, and added a penalty function for the ith AP of the Euclidean distance. Here comes a general introduction to the SRL-KNNs algorithm.

Assuming that the number of available APs is N, the fingerprint obtained at the ith RP at its physical location $l_i(x_i, y_i)$ is denoted as $f_i = \{F_1^i, ...F_N^i\}$ and the Euclidean distance between the test point and the ith RP is expressed as follows:

$$D_l^i = \sqrt{\sum_{j=1}^{N}(F_j - F_j^i)} \quad (1)$$

Where F_j is the RSS of the jth AP received at the test location, F_j^i is the RSS of the jth AP received at the ith RP. The modified Euclidean distance of the SRL-KNNs algorithm calculated as follows:

$$\overline{D_l^i} = \frac{W_l^i \times D_l^i}{\sum_{i=1}^{M} W_l^i} \quad (2)$$

$$W_l^i = \exp\left(\frac{(x_i - x_{pre})^2 + (y_i - y_{pre})^2}{4\sigma^2}\right) \quad (3)$$

Where M is the total number of RPs in the fingerprint database in the theory, while in this paper is the number of RPs in the reduced area from the first step. W_l^i is the penalty function for the ith RP, and (x_{pre}, y_{pre}) is the last position of test location, σ is the maximum distance which the user can move in a consecutive sampling time interval Δt. The penalty function obeys the Gaussian distribution with the average of (x_{pre}, y_{pre}) and the standard deviation is σ .Therefore, the function of W_l^i is actually to limit the possible position of the test point to a circular area in which the most recent previous position is the center and σ is the radius. The RP outside the circular area is not directly culled, but the weight is small. The unknown location l is determined through a weighted average of K nearest neighbours as follows

$$l = \frac{\sum_{j=1}^{k} \frac{l_j}{\overline{D_l^j}}}{\sum_{j=1}^{k} \frac{1}{\overline{D_l^j}}} \quad (4)$$

Where $\overline{D_j^i}$ is the modified Euclidean fingerprint distance which was presented in (2).

III. SYSTEM MODEL

Fingerprinting based position includes two stages: online and offline, as mentioned in Sect.1. The overview is shown in Figure 3.

Since each representative AP selected by users' position is different, we need to combine all possible combinations. It is shown that the number of all combinations of k (k < n) APs is taken from n different APs, and is represented by $C(n,k)$.Thus the original fingerprint database is changed to $C(n,k)$ $m \times k$ dimensional matrix. Of course, each row in the matrix corresponds to an actual location. In the online stage, a subset of APs is selected based on the minimum principle of RSS difference. The AP sequence is then matched against the ones in selected fingerprint map to reduce the area which is the first step location. The second step location is using the SRL-KNNs in reduced area.

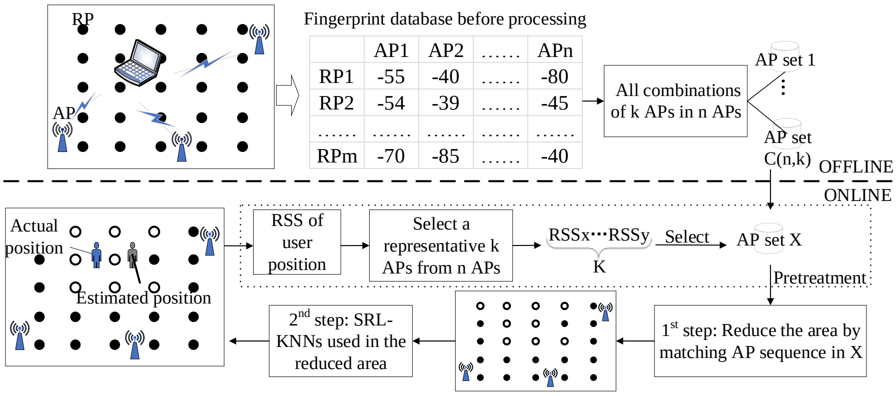


Figure 3.An overview of proposed reduced area algorithm indoor localization system.

A. Offline Construction of Fingerprint Map:

If the indoor environment is large with many APs, the RSS of some APs is weak in some fingerprints resembles noise. Experiments show that when the signal strength is below -78dB to -90dB, the weak signal collected by devices is not accurate, and the amount of redundant data is increased. Therefore, before the AP is selected, the noise APs should be removed first.

Suppose that there are 6 APs with reliable RSS. If 4 APs are selected, the original fingerprintwill forming into $C(6,4)=15$ fingerprint maps, and each fingerprint map is named with a serial number of 1~15. However, the AP set cannot be used for sorting. Since all the APs of each RP are combined, but each RP has its best combination, which caused some AP sequences with unreliability. As shown in Figure 2, RPs at box A and circle B, if the front 4 APs are selected, that is, in the NO. 1 fingerprint map. Then the fingerprint at A is (-43, -67, -35, -50) and fingerprint at B is (-49, -38, -64, -63). It is obvious that for A, the AP sequence composed of the first four APs is highly reliable, but the AP sequence at point B is unreliable in NO. 1 fingerprint map, and should be removed. After removed these AP sequence like B, then sort the RSS in each map. Take the NO.2 fingerprint map (which selected AP is AP1, AP2, AP3, AP5) as an example, as shown in Figure 4.

During the experiment, remove the RPs that the RSS less than -85dB and the difference between the adjacent RSS in the AP sequence are less than ±5dB in every sub-fingerprint map.Moreover, the physical location map should be updated accordingly.

The original NO.2 map

NO.2	AP1	AP2	AP3	AP5
RP1	-55	-40	-29	-73
RP2	-54	-39	-31	-68
……	……	……	……	……
RPm	-52	-61	-70	-40

AP set 2

RP1	3	2	1	4
RP2	3	2	1	4
……	……	……	……	……
RPm	1	4	2	3

Figure 4. The original NO.2 fingerprint map and the AP set 2.

B. Online Location:

(1) Pre-treatment of Online Positioning Point

Received the fingerprint sent by the user, and then select the representative APs. There is also assumed that 4 APs are selected from 6 APs. In order to make sure that the difference of RSS between the selected 4 APs is the largest among all APs. Firstly, sorted the RSS of 6 APs and the five differences between the RSS of the neighbouring APs, and the smallest difference is merged into one class. By analogy, until merged into four categories, selected one representative AP from each class and arranged into AP sequence. It is worth mentioning that the results of clustering using K-means algorithm are not ideal, and the difference between adjacent AP is not the largest among the clustering results. This may due to the K-means algorithm is more suitable for clustering large amounts of data, such small clusters are prone to over fitting, and when the RSS of the two APs is same, the program will appear infinite loops.

The selected APs are used to match AP sets for position. For example,if the selected AP is (1, 3, 4, 5), and then the set used for positioning is NO. 7.

(2) Position Estimation

The first step of position is to reduce the location area, effectively solving the difference between the signal space and the geospatial distance mentioned in Sect. 1. According to the Pre-treatment, selecting the same order RPs as AP sequence in the selected AP set, and thus the area formed by the selected RPs is the reduced area. This reduces the computational complexity of the next positioning step. Thus improve the speed of the positioning algorithm.

In the second step, when using the SRL-KNNs algorithm to locate, the first position is estimation by WKNN, and the value of σ in formula (3) is 2m. And only the RPs in the reduced area needs to be traversed when calculating the Euclidean distance.

IV. RESULT

A. Experimental Setups

The experiment has been carried out in the laboratory with area of $16\times 20m$ in college of Electronic Information Engineering, Tianjin Polytechnic University, as shown in Figure 5. Arrange 6 wireless routers (TP-LINK TL-WDR6500) as APs. The collecting device is Lenovo IdeaPad computer, and the RSS is obtained by the C# console program compiled by VS2013, the interface is shown in Figure 6. We collected 180 offline test points and 1.2m interval if without obstacles. It is collected 100 times at each RP and the data is automatically saved in Excel and then imported into MATLAB (2017b) for filtering. During the collection process, people in the laboratory walked from time to time.

Along the trajectory shown by the dotted line in Figure 6, we select 57 points as test points on the trajectory, and each test point collected 1 s, which is more suitable for actual positioning. Note that, because of the instability of WiFi transmission signal and environmental factors, there may be some samples from APs that are not be received 1 or 2 times, but other times can receive RSS. Instead of setting these RSS to -100dB, in this paper we remove the sample data directly.

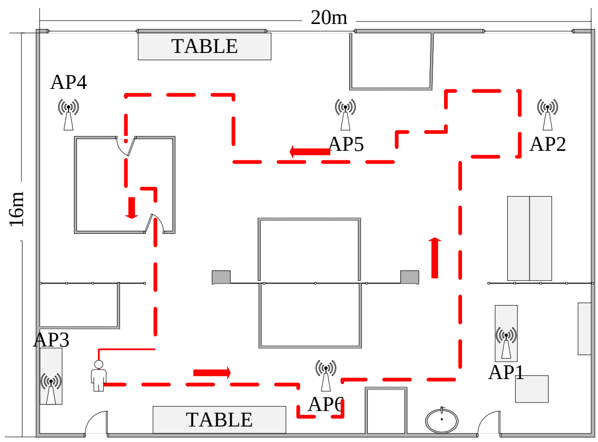


Figure 5.Floor map of experimental site. The dotted line is the online test trajectory.

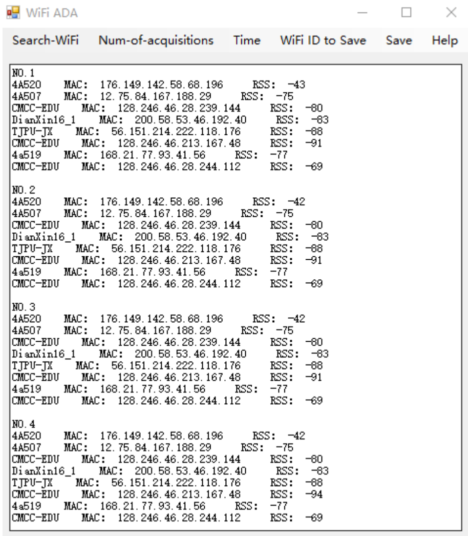


Figure 6. Acquisition interface in VS2013.

B. Results and Analysis

In order to test the performance of the two-step positioning estimation algorithm separately, the analysis is divided into two parts as following.

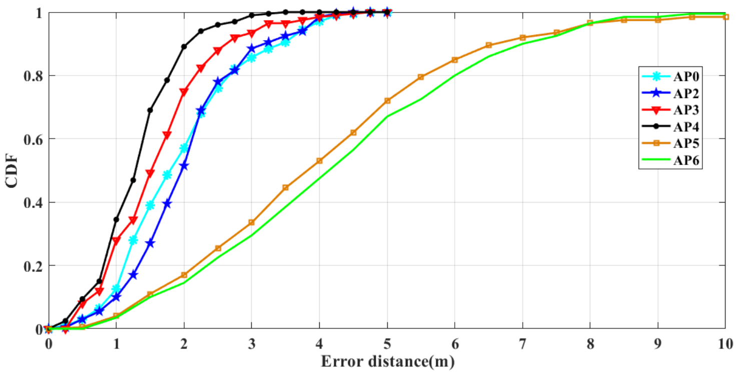
(1) Test of first step: reducing area

Using the method of the control experiment, the selection of 0 AP (means no AP selection is performed) compared with the selection of 2 ~ 6 APs. There is no case of selecting 1 AP, because at least two APscan be compared. The second step of the position algorithm achieved by WKNN. Figure 7(a) shows the cumulative distribution function (CDF) of positioning errors. Obviously, the selection of 4 APs achieves the best performance of accuracy among different selection of APs, and the maximum error is 3.2m. And the selection of 6 APs is the worst, which is consistent with the above analysis: not the more APs are selected, the higher the positioning accuracy. If AP selection is not performed, the maximum error is 4.3m. It can be concluded that reduced the positioning area by AP selection greatly improve the positioning accuracy. But decide the number of choosing APs also requires a combination of positioning time considerations.

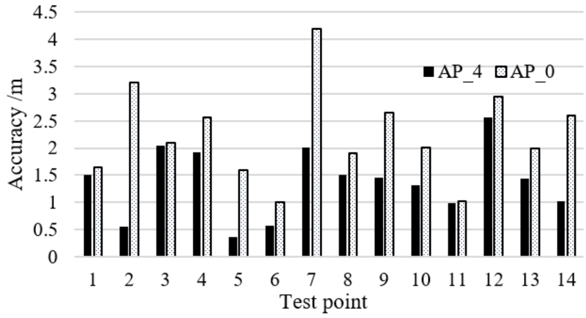
Figure 7(b) shows the comparison of accuracy between selection of 4 APs and 0AP at several single test points. It can be concluded that the different of positioning errors at some points are slight, while some vary, which due to the separate of the signal space and the physical space.

Figure 7(c) shows the affective of the reference point number to the accuracy. When the offline reference point is reduced, the 4APs selection algorithm has higher positioning accuracy than the 0AP algorithm. This is very beneficial for reducing overhead when offline surveys and needs further research.

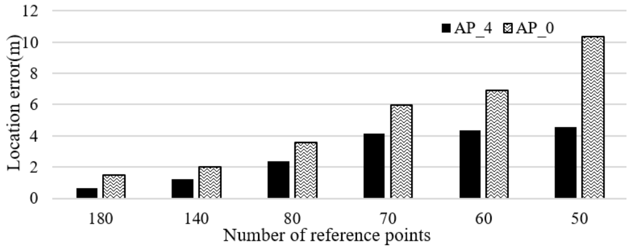
Table Ⅰ shows the location time-consuming of different AP selections. The time loss without AP selection is the largest, because all the RPs are traversed when calculating the Euclidean distance. Reducing the area through the selection, results in a reduction of calculation. Selecting 4 APs achieves a balance between positioning time and accuracy. Therefore, after the analysis of time-consuming and position accuracy, choose the selection of 4 APs for the first step of positioning in the next experiment.



(a)



(b)



(c)

Figure 7. (a) CDF of localization errors of different selection of APs. (b) Accuracy of 4 APs and 0AP at several single test points. (c) Accuracy of affective with different reference point number.

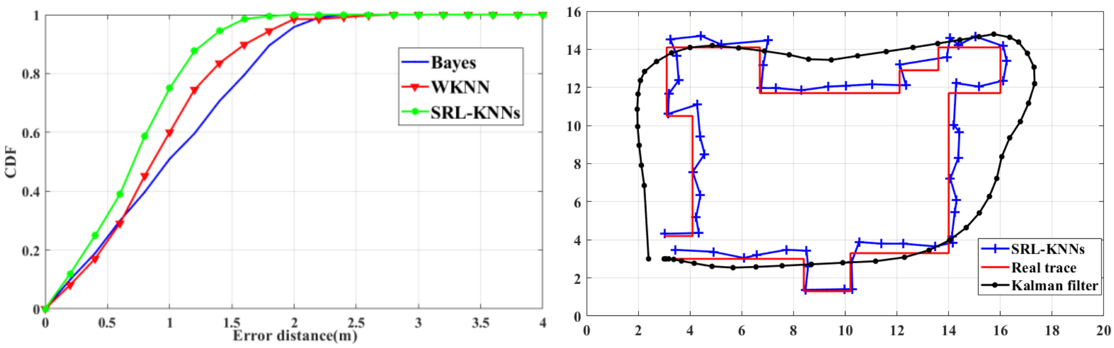
Table Ⅰ.Time consumption

Select_AP	0	2	3	4	5	6
Time consumption(s)	6.53	4.02	3.66	2.13	1.41	1.20

(2). Test of second step: SRL-KNNs in reducing area

After accomplished the first step of positioning by the selection of 4 APs, different positioning algorithms estimate the position in the reduced area. Figure8 (a) shows the CDF of SRL-KNNs algorithm compared with Bayesian and WKNN algorithms. The SRL-KNNs algorithm achieves better location effect with the average location error 0.74m, 75% of the location error under 1m. The maximum location error is 1.6m, while the Bayesian and WKNN algorithm is 2.4m and 2.6 respectively.

Figure 8 (b) shows the comparison of the trajectory between the SRL-KNNs algorithm and the Kalman filter. The two-step algorithm of this paper is basically consistent with the real trajectory. Since the SRL-KNNs algorithm only uses the previous position to form a soft range limiting scale factor, instead of directly including the historical position in the current position calculation. Therefore, the location error of the historical position makes little impact on the current positioning accuracy.



(a) (b)

Figure 8. (a) CDF of localization errors of SRL-KNNs, Bayesian and WKNN. (b) Compare of trajectory between SRL-KNNs and Kalman filter.

V. CONCLUSION

This paper proposed a reduced location area algorithm achieved by the two-step positioning method based on AP sequence and SRL-KNNs. The fingerprint database is constructed by using AP sequence reduced the error caused by signal fluctuation and device diversity. At the online stage, two-step positioning method has achievements in every step. Step 1: Reduced the positioning area, combine the signal space and the physical space. Step 2: Use the SRL-KNNs algorithm in the reduced area, achieves higher location accuracy and lower time-consume. Experiments results have shown that the reduced location area algorithm achieves an average localization error of 0.74 m with 75% of the error within 1m. In addition, the experiments results shown that when reduce the number of reference points, the change of positioning accuracy with AP sequence is not significantly. Therefore, the subsequent research is to reduce the workload of offline fingerprint database establishment with the premise of high location accuracy.

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