Radio-Map Search Algorithm Based on Steepest Descent Principle

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Abstract. For most of the Ad-Hoc systems, position information is very important. Indoor scenario is a blind area of Global Navigation Satellite System (GNSS) service, which affects the application of Ad-Hoc technology. Fingerprint positioning technology is one of the most popular indoor localization methods. Searching strategy is one of the key techniques of fingerprint positioning. Because the data amount of the radio-map, which is used as the database of the system, is very big. Currently, the main accelerating measure of radio-map searching is clustering. But clustering brings some problems to the system, such as jittering and jamming. This paper proposes a novel radio-map searching strategy. Based on the steepest descent principle, the searching order is changed in the proposed method, compared with traditional clustering-positioning strategy. Thus, the radio-map is used in one piece, which is different from the traditional clustering-matching strategy. Simulations and experiments verified that the positioning accuracy of the proposal is better than that of the traditional method.

Keywords: Database searching · Indoor positioning · Fingerprint localization
Steepest descent principle

1 Introduction

Fingerprint localization technology is widely studied in indoor positioning area, because it utilizes the shadowing and reflection of complex indoor scenarios, which blocks the application of traditional positioning technologies, especially the GNSS service. Generally speaking, fingerprint technology is a matching process, between user calibrated sample and a big database, which is named as the radio-map. As the data amount of the radio-map is extremely large, an efficient searching method is definitely important for a fingerprint positioning system. Currently, the most popular searching method is clustering. The radio-map is arranged into several clusters, before positioning process. The user equipment (UE) has to identify which cluster is it in. Thus, the

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positioning process is divided into two steps: clustering and matching. Clustering strategy is widely studied. In paper [1] three clustering methods, K-means, affinity propagation and fussy C means, are summarized in order to make balance between the positioning accuracy and the computing complexity. Received signal strength (RSS) based clustering and micro-cell based radio map construction methods were combined in paper [2] to reduce the computational burden of fingerprint positioning. Clustering and principal component transformations in which the number of training data is reduced, compared with traditional system is used in paper [3]. Even in compression perception based fingerprint positioning system, clustering is necessary. [4] Paper [5] presents a support vector machine -C algorithm which enhances the positioning accuracy for clustering. A partitioning machine learning classifier method includes a clustering task and a classification task is proposed in paper [6]. Clustering can be seen as a kind of initial positioning which provides the final positioning results in some applications [7]. In paper [8], K-Melodies and signal feature extraction algorithms are used to reduce the complexity of clustering. As mentioned in paper [9] domain clustering can be used for indoor position estimation, which can enhance the positioning accuracy. Clustering is one of the most effective methods, especially in floor recognition process. [10] Dynamic clustering is also used in unmodified fingerprint systems. [11] To enhance the robustness of clustering algorithm, paper [12] proposed a novel grid estimation method. But clustering-matching scheme also brings some problems. Firstly, when a user is at the seam of two or more clusters, the positioning result may jitters between the neighbor clusters. This is caused by the Ping-Pong problem of identifying, as the cluster heads of nearby clusters are mostly similar. Secondly, for the same reason, when a user is moving from one cluster to another one, the positioning result may be jammed in the former cluster, which causes the positioning delay. Furthermore, different clustering methods have different problems. If the clusters were arranged manually, the distinction of signal feature space would be affected. If they were arranged automatically by clustering algorithms, the spatial distinction would be affected. This paper provides a novel radio-map searching strategy, which utilizes the prior information of the user's track. There is no necessary to divide the radio-map into pieces in the proposal, the searching order follows the steepest descent principle.

The remainder of this paper is arranged as follows. Section 2 introduces some related knowledge of this paper. Section 3 proves the main algorithm of the proposal. The simulation and experiment are illustrated in Sect. 4, followed by the conclusion and acknowledgment part.

2 Related Works

Fingerprint positioning technology is very suitable for indoor applications, because it utilizes the non-line of sight signal feature, which causes traditional positioning method fails. Fingerprint positioning technology has two steps in application: offline process and online process.

In offline process, the database is established, which is called the radio-map. Radio-map is formed by a large number of reference points (RP). Each RP records the mapping relation of the signal feature and its physical location. The RPs are mostly organized uniformly in the service area. And each RP is extracted by a variety of measurement samples.

The database will be used in online process. The user will use the real-time signal feature, to compare with the RPs in the radio-map. The Euclidean distances will be calculated to characterize the similarity between real-time signal feature and the RPs, as the following equation.

$$D_{Ei} = \|\mathbf{r}_{mi} - \mathbf{r}_r\| \tag{1}$$

Where $\mathbf{r}_{mi}$ means the RSS vector of the i-th RP, and $\mathbf{r}_r$ is the RSS vector of real-time signal.

The nearest K RPs in Euclidean distance will be selected to estimate the user's position. The physical locations of the RPs will be averaged as the final positioning result. This method is called the K nearest neighbor (KNN) algorithm, which is widely used in fingerprint positioning.

Clustering process is similar with positioning process. The RPs are arranged in groups, according to their signal features or their spatial distribution. The mean value of RSS vectors of the RPs in each group is calculated as the cluster head. Cluster heads are used as an upper level RPs, KNN algorithm is also used in cluster identifying, but here K equals to 1. After the clusters identify process, only the RPs of the selected cluster would be used in position calculation. Thus the whole positioning process is divided in two levels: clustering and positioning.

3 Steepest Descent Based Radio-Map Search Algorithm

The steepest descent principle based searching strategy in this paper is proposed based on the following two prerequisite:

(1) The track of the user is continuers;
(2) The Euclidean distance has a monotonous relationship with the physical distance, as shown is Fig. 1.

The simulation scenario of this figure is a single room with 4 APs. Assuming the radio-map is tiled on the X–Y side. The TP is at the (50, 50) point, which is shown by the arrow. The figure illustrates the Euclidean distances between the TP and all the RPs, indicated by the Z-axis. It can be seen that further RPs have bigger Euclidean distances.

The proposed algorithm searches the nearby RPs of the prior-known position, such as the latest position or the forecasted position of the user, in circle order. During the searching process, the K nearest RPs in Euclidean distance would be recorded and refreshed until they are fixed still for a certain time. Before that, the searching center would be changed step by step. At the first step, the prior-known position is selected as the center of the circle. And in the following steps, the center of the circle is the RP that has the smallest Euclidean distance with the TP in the last circle. The searched RPs will not be searched any more. The workflow of this algorithm is shown in Fig. 2.

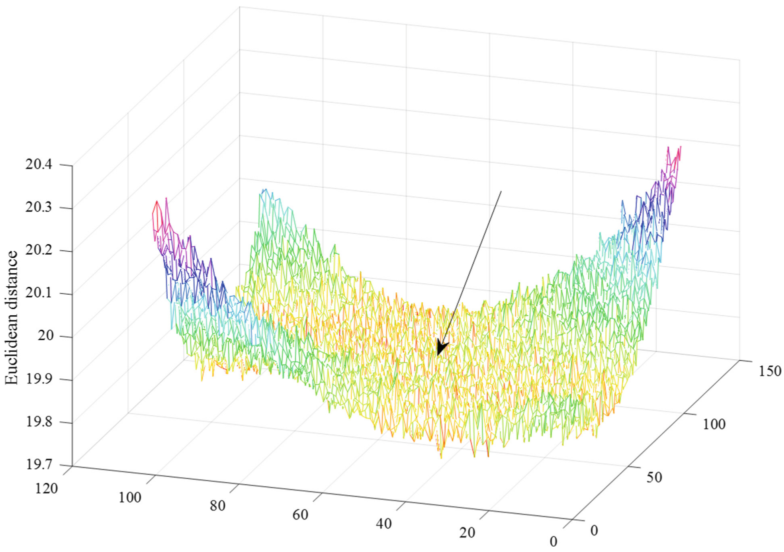

Fig. 1. Monotonous relationship between the Euclidean distance and the physical distance.

Variable N_c in the figure is the searching counter of the algorithm, if this counter reaches a certain threshold L, the searching process stops.

An example of the searching order of this paper is shown in Fig. 3. The radio-map is illustrated by the grids at the bottom of the figure and the latest positioning result of the user, which can be seen as the prior information, is marked by red color and shadows. The searching process is divided in steps, which are shown in different levels and distinguished by different colors. The grids of each level indicate the RPs that covered by this searching step. The color depth of each grid indicates the Euclidean distance between the corresponding RP and the TP. We can clearly find the moving track of the searching center, which are also highlighted in the radio-map by corresponding colors. When the RP selection register keeps unchanged for L steps of searching, as shown by the "Step 8 and so on", the searching process stops.

4 Simulation and Experiment

The effectiveness of the algorithm is verified by simulations. The simulation scenario is established based on cost 231 model. The building structure is shown in Fig. 4. 6 rooms and 1 passage is included, 4 APs are deployed uniformly in the building. Totally 696 RPs are arranged into 7 clusters, according to the structure of the scenario.

Clustering is not necessary in the proposed system, because the scenario is not very big. But in order to compare the performance of the proposal and the traditional clustering-matching strategy, the radio-map is also clustered, as mentioned before. In the simulations, clustered radio-map is only used in traditional system as a compare group. The positioning accuracy simulation is given in Fig. 5.

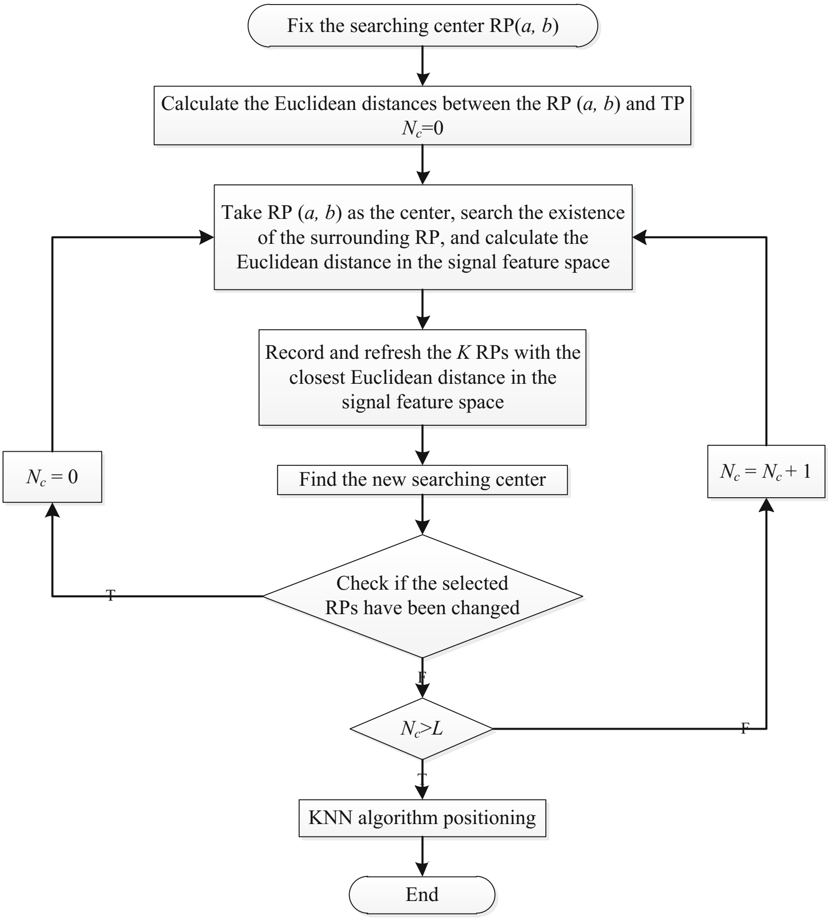

Fig. 2. The workflow of the proposal.

In the searching speed simulation, *RNTF* (RP Number Till Fixed) is used to evaluate the searching speed, which indicates the RP number that need to be covered until the location is fixed. For different searching strategy, the average *RNTF* of the simulation is recorded, as shown in Fig. 6.

It can be seen that when $L = 5$ or $L = 10$, the proposal performs better than the traditional clustering-matching strategy. When L equals to 1, the accuracy is the worst, and the searching speed is nearly the same with traditional algorithm. The increase of L brings no significant accuracy enhancement when $L > 5$, but only brings searching speed decrease. Positioning without clustering is not the most accurate method, and it has to search all the RPs, which makes it the slowest one among all the mentioned methods.

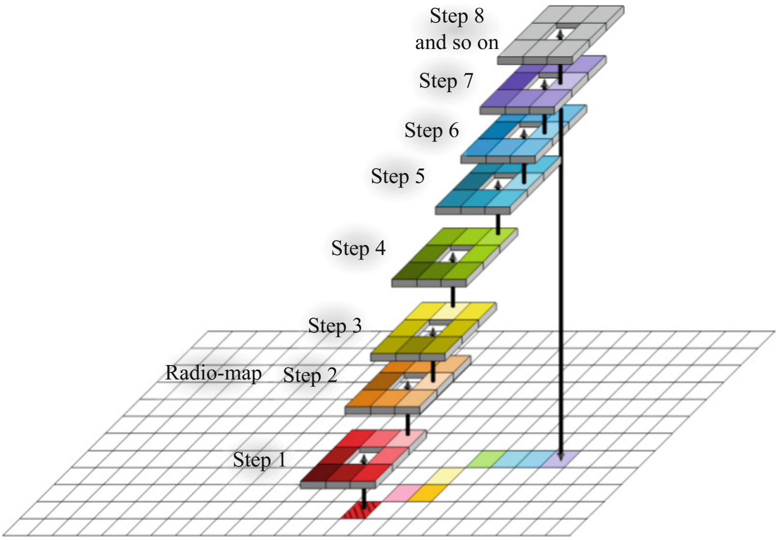

Fig. 3. Searching order of the proposal. (Color figure online)

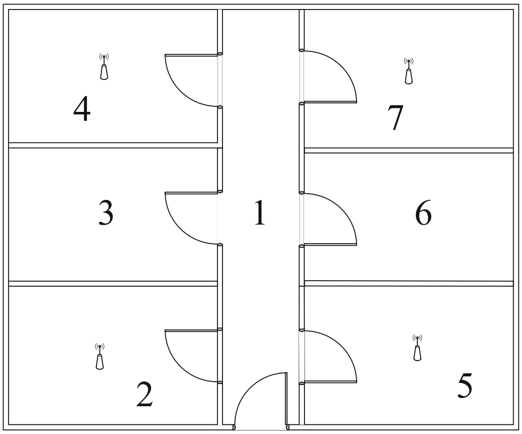

Fig. 4. Simulation scenario.

In order to further verify the system performance, measured data is used in the hardware experiment. The experiment scenario is shown in Fig. 7, and the track of the user is illustrated by the red dots. The experiment results are shown in Fig. 8.

It can be seen that the positioning accuracy of the system is related with the parameter *L*. An appropriate *L* value could ensure the system performance and reduces the positioning error. If *L* is too small, the searching process would be stopped too early before it can find the right RPs. Contrarily, if *L* is too big, the searching speed would be affected.

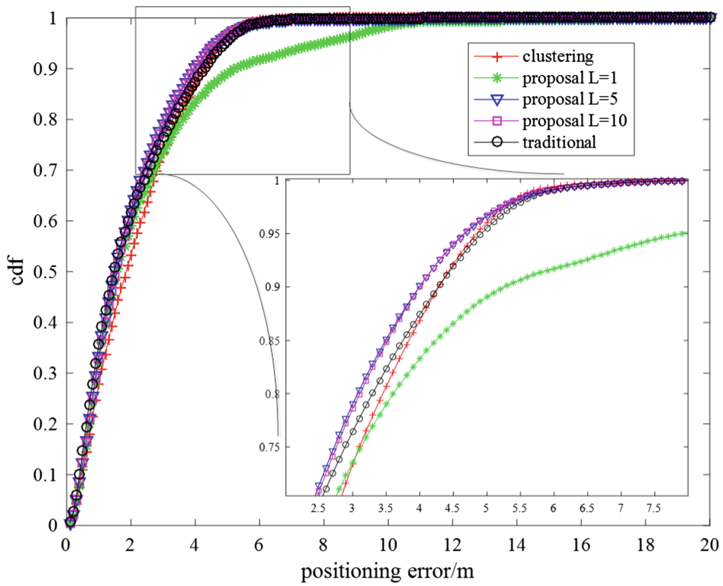

Fig. 5. Positioning accuracy simulations.

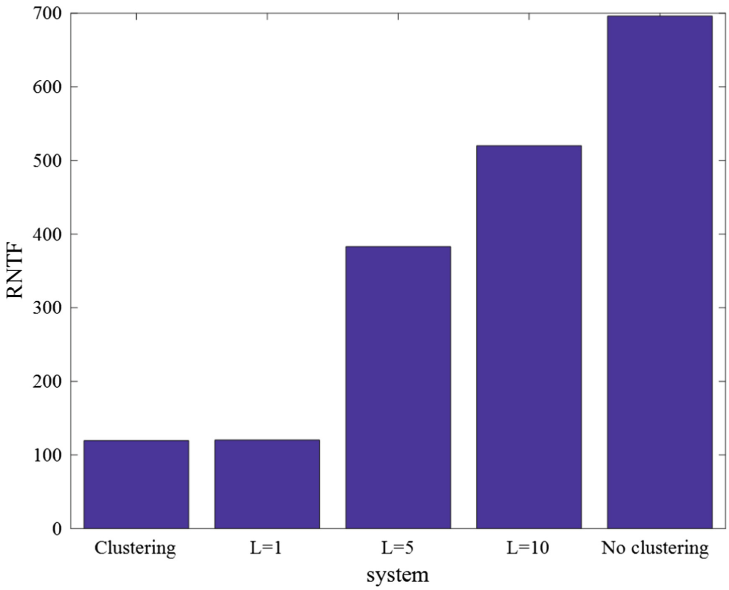

Fig. 6. Search speed comparison.

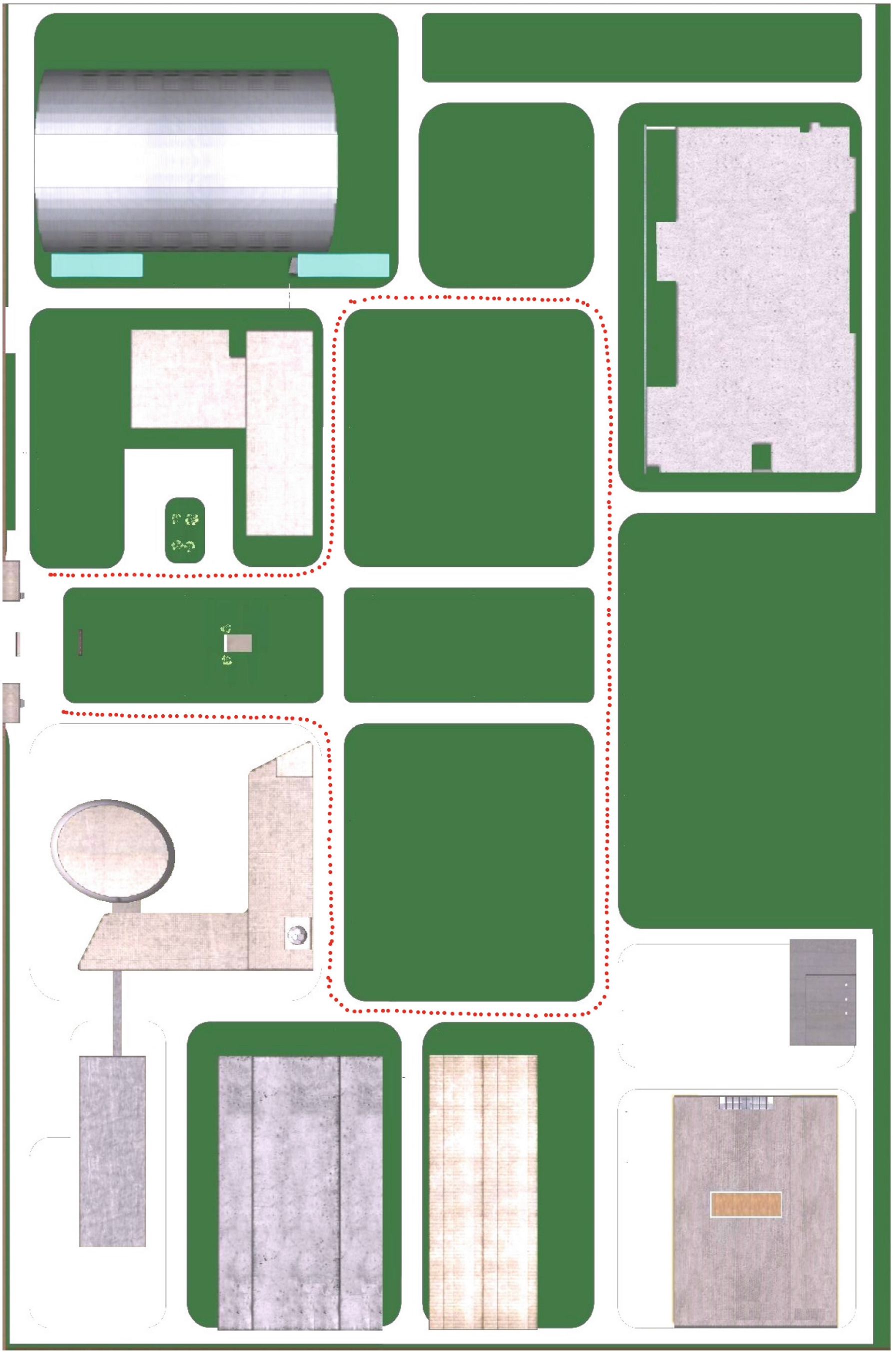

Fig. 7. Experiment scenario. (Color figure online)

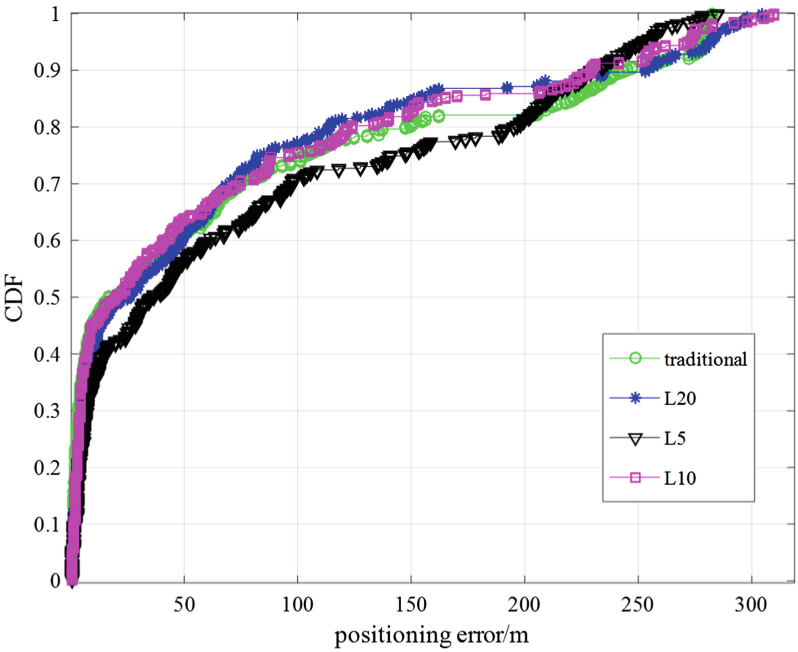

Fig. 8. Experiment results.

5 Conclusion

This paper proposes a novel database searching strategy. This strategy helps the UE to refine the useful information effectively in fingerprint positioning. The proposal utilizes the prior information of the user's track, and searches the radio-map diffusion-liked, instead of the traditional clustering-matching strategy. Simulation shows the proposal could enhance the positioning accuracy and keeps the searching speed in an acceptable level.

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