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Original Article

A Robust RSSI Fingerprint Localization Method in Wireless Local Area Network

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Abstract *- The Received Signal Strength(RSSI) based location fingerprint positioning technology under the wireless local area network(WLAN) has become a research hotspot. For indoor positioning, using wireless networks for location calculation is cost-effective and easy to deploy with high positioning accuracy. However, there are still some problems in the indoor fingerprint positioning technology based on RSSI signal: in the offline stage, on the one hand, the indoor environment is complex and has undergone changes, the received signal has spike noise during the acquisition process, which will make the reliability of the collected fingerprint collection change over time. As a result, it is difficult for users to detect the RSSI signal transmitted by the Access Point(AP) when they are online, which reduces the accuracy of indoor fingerprint positioning. It is also different, and even the status of some APs will change when they are online, reducing the robustness of fingerprint positioning. In the online stage, the traditional fingerprint positioning method needs to traverse the entire database when calculating the coordinates in the positioning stage, which in turn brings a lot of redundant calculation overhead and mismatches, decreasing positioning accuracy. Therefore, this paper designs a prototype system DeLoc for denoising. An AP entropy based on Gaussian detection is proposed for the offline selection and online filtering of APs. The average positioning error of DeLoc under different grid sizes and different AP numbers is verified by simulation experiments, and compared with traditional methods, DeLoc, designed in the paper, is robust and stable.*

Keywords *- Indoor localization, Robust, Fingerprinting, AP detection, Wireless local area network.*

1. Introduction

Internet of Things technology has greatly impacted people's lives. At the same time, the introduction of mobile terminal devices has further increased people's demand for Location-Based Services (LBS) applications [1-5]. The positioning technology based on satellite communication can effectively meet users' needs for outdoor positioning, but when used indoors, the positioning capability is greatly limited. The indoor fingerprint localization method in the WLAN environment realizes the localization of the target through the work of the offline stage and the online stage [6,7]. In the offline phase, a reference node is set up indoors. The RSSI signals of each indoor AP are collected on the reference node to construct a location fingerprint, and a location fingerprint database is established. When online, the target collects the RSSI signal of the current location and sends it to the background server and fingerprints. The database is matched to complete the position estimation of the target. The positioning accuracy of the fingerprint positioning algorithm in the WLAN environment largely depends on whether the offline training data and the online collected data satisfy the same distribution characteristics. On the one hand, in the process of RSSI fingerprint collection, due to the interference of the environment, there is spike noise in the RSSI signal [8], which leads to the matching of APs far away from the physical location of the target during online positioning, which reduces the positioning accuracy. On the other hand, the traditional fingerprint positioning method requires that the AP detected online is the same as the AP in the offline fingerprint database [9], and the online fingerprint vector is used as a matching parameter to match the fingerprint database. However, due to the interference of spike noise, online users cannot detect some of the AP signal, online data, and offline fingerprints, which are difficult to match [10], which reduces the robustness of the fingerprint positioning algorithm. Moreover, in the positioning stage, the entire database must be traversed when calculating the coordinates, which is time-consuming and labor-intensive, resulting in reduced positioning accuracy. DeLoc for the problem of spike noise, AP state change and excessive computational overhead in the positioning phase of RSSI signals in a complex indoor positioning environment. Our advantages of the paper are:

- Aiming at the problem of spike noise in RSSI signal acquisition, a reference point torus intersection localization method based on robust feature extraction is proposed.

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- Aiming to address the problem of selecting indoor APs to establish a fingerprint database and the decrease of robustness of fingerprint location caused by the change of online AP state, an AP entropy weight fingerprint location algorithm based on Gaussian detection is proposed.

2. Method

2.1. Processing of DeLoc

In the indoor positioning area, theoretically, any target in the positioning area can be represented by position coordinates. However, due to the influence of weights and noise, there must be errors in the positioning process. Generally speaking, a mobile terminal's RSSI signal range is -95dbm to -60dbm. Due to the influence of peak noise, the RSSI signal is attenuated to -95dbm. In addition, the terminal cannot detect such RSSI signals, and the AP is lost. In this way, the dimension of the online RSSI signal vector is inconsistent with the offline fingerprint data. The system will lose the online positioning function if it is not processed.

To address the above problems, the paper designs a torus intersection localization algorithm based on robust feature extraction. The processing of DeLoc is as follows:

- In the measurement and acquisition of RSSI signal, sparse spike noise reduces the positioning performance. Therefore, we first reduce spike noise in offline and online RSSI signals.
- Some APs cannot be scanned online and are affected by spike noise. Therefore, the RSSI value of APs that cannot be detected online or are unstable should be set to 0.
- Reorder online RSSI fingerprint vectors in descending order of RSSI value from large to small.
- By setting the threshold parameter, use the first K RSSI signals, not 0, in the sorted online RSSI signal vector.
- Each reference point torus contains some points that are closer to the target. These RPs are not satisfactory enough. The intersection of the reference point torus and the reference point in the intersection is used as the final matching reference point for the target.
- Calculate the sub-estimated positions of users under each AP according to the intersection of the reference point torus, and then use the AP-weighted nearest neighbor positioning approach to calculate the final location of the point to be located.

2.2. Entropy Weight

This method is divided into two stages: AP selection for the offline stage and online AP filtering. 1) In the offline stage, an offline AP evaluation index is designed according to the characteristics of information entropy, the non-uniform quantization RSSI information entropy and the AP with large entropy are selected to establish the RP location fingerprint database; in the localization, area predesignates the AP state monitoring point, collect the RSSI signal of each AP on the SP, and obtain the RSSI model parameters of the offline state of each AP on the SP; 2) in the online stage, the positioning system collects the RSSI signal on the SP, and based on the Gaussian RSSI signal The detection model detects the state changes of online APs, filters the APs that have changed online, and uses the signals of APs that have not changed state to estimate the target.

3. Experiments

3.1. Experimental Setup

In the simulation, the indoor propagation model of the RSSI signal is used as the RSSI signal model of the AP to establish the location fingerprint database. According to the actual RSSI measurement value, if the value of the RSSI is less than -95dbm in some positions, it can be considered that the AP is not detected. The simulation environment uses the following settings: the grid size of two adjacent reference points is 5m, and the number of APs is 8. The parameter k of the proposed algorithm (DeLoc) is set to 3.

3.2. Evaluation

Figure 1 is the positioning errors of different algorithms under the influence of noise. The random noise intensity ranges from 10dbm to 25dbm. The results of experiments demonstrate that the performance of all algorithms increases with the decrease of noise. The reason is that the smaller the noise, the smaller the probability that the localization algorithm will match the reference point farther away from the target. When the noise is slight, the positioning accuracy of all algorithms is not very different, but as the noise becomes larger, the performance of these algorithms gradually differs. Different from these comparison methods, our DeLoc uses APs with larger RSSI online to locate and filter out sparse spike noise. Figure 2 is the curve of the average positioning error with the grid size of two adjacent reference points. The size of the grid decreases from 2m to 10m. When the grid increases, the accuracy of all comparative positioning algorithms decreases.

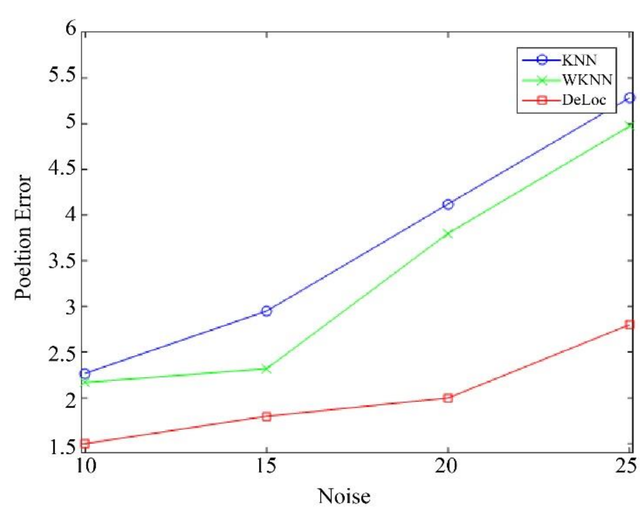

Fig. 1 The relationship between positioning error of different methods

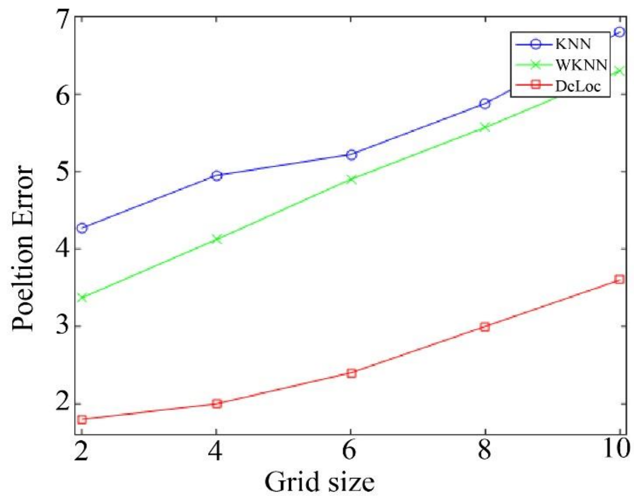

Fig. 2 The relationship between positioning error with grid size of reference points

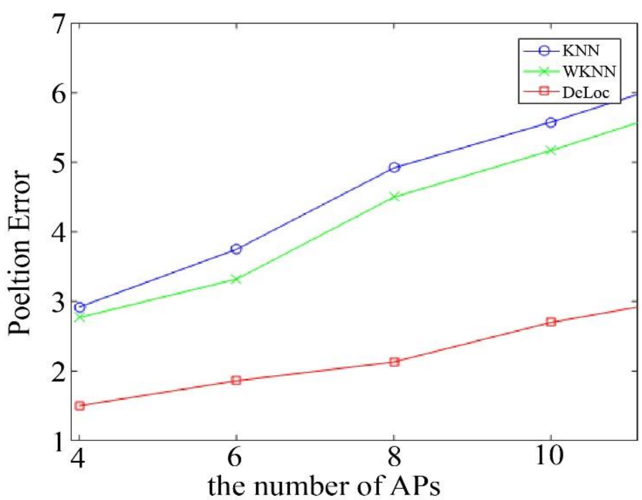

Fig. 3 The relationship between positioning error and the number of APs

With the increase of the grid size, the fineness of the grid becomes larger, and the positioning error will inevitably increase. DeLoc uses k reference point torus intersections for matching and uses the intersected reference point as the nearest reference point, which can reduce the possibility of matching distant reference points. Figure 3 shows the relationship between the average positioning error and the number of APs whose status has changed. The number of APs is from 4 to 10. The APs whose online status has changed are randomly selected from the deployed APs. The performance of all algorithms degrades as the number of APs with changing online status increases, and DeLoc outperforms the other four algorithms. When there is no AP state change online, the average error of DeLoc is smaller than that of other algorithms, illustrating that DeLoc also has better positioning accuracy in the normal environment. Because DeLoc uses the AP entropy weighted similarity distance to match the neighboring reference points, it can filter APs whose online status changes during matching and determine their importance in the similarity distance according to the performance of the online normal APs, reducing the matching geographic location. In addition, DeLoc considers the influence of AP on location estimation and uses AP's improved entropy weight to estimate the target. The weight of AP is more reasonable and improves the localization performance.

4. Conclusion

This paper studies the problems affecting the accuracy and robustness of indoor fingerprint positioning systems based on RSSI and proposes DeLoc. It contains an AP entropy weight fingerprint positioning algorithm to solve the problem of offline AP selection and online AP state change in the real environment. The average positioning error of DeLoc under different grid sizes and different AP numbers is verified by simulation experiments, and compared with traditional methods, DeLoc designed in the paper has higher robustness and practicality.

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