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Original Article

Reliable RSS Indoor Location Systems Based on Signal Distribution

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Abstract *- With the in-depth development of the Internet and information technology's rapid development in today's world, location-based services are gradually entering people's daily lives. Indoor positioning has gradually penetrated all aspects of social life. However, the current indoor positioning technology still has significant shortcomings in positioning accuracy. This paper will explore indoor localisation methods to increase the accuracy of indoor localization, reduce the cost of positioning, and decrease the power consumption of equipment. In this paper, we propose a more stable based on RSS fingerprint localization algorithm for signal distribution and design a reliable RSS indoor positioning system, Wi-SD. Experiments show that Wi-SD has better stability and accuracy.*

Keywords *- Positioning, Signal distribution, Similarity matching, RSS, Fingerprint.*

1. Introduction

Location-based services have gradually become indispensable in daily life [1-5] and are generally divided into outdoor and indoor positioning according to implementation scenarios. Due to the deployment of satellite positioning systems, outdoor positioning and navigation have been well applied, and the accuracy can reach nearly a sub-meter level[6, 7]. With the wide deployment and widespread application of wireless network environments, researchers use wireless signal fingerprints for matching and positioning methods. The basic idea is to use the spatial differences of access points (APs) in different locations and use the reference point's wireless signal characteristics as the physical location's characteristics to determine the location [8]. This feature is called Fingerprint, and Received Signal Strength (RSS) is a typical fingerprint feature. This fingerprint-based method usually includes two stages: offline fingerprint map collection and training and online perception position positioning. In the offline stage, RSS fingerprints and location tags are collected through on-site surveys to form a fingerprint database [9, 10]. In the online stage, the user is located by matching the fingerprint observations with the received wireless signal database. However, despite extensive research, indoor localization using RSS often produces large localization errors and has not yet been widely used. The main obstacles are two aspects, which are expensive field survey training efforts and unreliable accuracy [11, 12]. This paper proposes an effective indoor localization method, Wi-SD, a purely WiFi fingerprint-based indoor localization system. It reduces the ambiguity of nearest neighbor selection in spatial and temporal domains during localization, thereby achieving reliable performance. This paper analyzes the spatial characteristics of RSS values in depth to enhance the sampled fingerprints. Specifically, using multiple adjacent location APs can better demonstrate the spatial relationship of RSS and have better robustness. For our Wi-SD, we use signal distribution to improve positioning accuracy. The signal distribution can demonstrate the similarity of RSS between neighboring positions.

The significant contribution of this article lies in the following:

- Signal distribution demonstrates the similarity of wireless signals between neighboring locations. Compared to directly using RSS as a fingerprint, this can more effectively reduce the uncertainty of signals in the spatio-temporal domain, thereby improving positioning accuracy.
- Verify the performance of Wi-SD through experiments and conduct thorough experiments in various environments. The results show that Wi-SD achieves significant performance gains without additional information or limitations for the user.

2. Our Method

2.1. Limitations of Fingerprint Location

Existing studies have shown that there are usually significant differences in the wireless signal values observed by different observation equipment at the same location for the same AP point. In the process of fingerprint positioning, whether it is the offline fingerprint data collection stage or the online location request stage, different mobile devices are currently used, and the resulting RSS observations will interfere with the accuracy of the positioning algorithm. To illustrate this limitation, we selected five different brands of smartphones in the laboratory, collected the RSS values of surrounding AP points for comparison, and repeated sampling 10 times for different APs at the exact reference location to obtain the average value. It is not difficult to find that the RSS values obtained from different wireless sampling instruments have significant errors, even under the same conditions. In actual situations, due to this difference, our fingerprint database is not universal, which greatly reduces the service life of the fingerprint database. In order to solve the above three problems, we propose a new concept of RSS fingerprints—signal distribution and design a reliable RSS indoor positioning system, Wi-SD.

2.2. Limitations of Fingerprint Location Algorithms

We know that the value of the traditional RSS fingerprint will change. However, experiments and data analysis show that the difference between signals received at adjacent locations will be relatively stable. This is because even though AP observations change with time, the RSS is in two similar directions and adjacent positions. The difference change between the signal values is relatively small, so we find a relatively stable intermediate quantity. Moreover, considering multiple locations around a location, we can get the RSS distribution law of an AP at this location. Although the RSS measurement value can be the same in different locations, the RSS distribution law of the two locations will be significantly different. When matching, the RSS observations collected by the unknown point are calculated. The vector matrix of the hierarchical distribution of all points on the map is calculated. Then, the similarity between this hierarchical distribution matrix and all the hierarchical distribution matrices on the map is calculated.

2.3. Framework of Wi-SD

For our Wi-SD, in the data training stage, store the collected Sampling data for each reference point in the fingerprint sets and then use the previous method to select a nearby point at each sampling point, calculate the hierarchical distribution matrix, and record the proximity of the hierarchical distribution matrix and the construction matrix. Point's RSS fingerprint information. On the user side, after collecting a fingerprint vector in an unknown indoor area, the user will traverse each sampling point in the database to match it. Assuming that the current location is matched, during the matching process, the user's fingerprint will be The adjacent location set used in constructing the hierarchical distribution matrix to construct each RSS fingerprint description and hierarchical distribution matrix and upload it to the server at the positioning end. At the positioning end, the server will calculate the similarity between the hierarchical distribution matrix constructed by the user and the hierarchical distribution matrix in the data. After the user fingerprint has traversed all the sampling points, the KNN algorithm is used to select K's nearest neighbors, then take the average of their horizontal and vertical coordinates as the coordinates of the positioning point, and the server will feed this average value as the final positioning result to the user as the positioning result.

3. Implementation

3.1. Parameters

Before experiments, there are some algorithm parameters that we need to select through experiments. These parameters include comparing methods for selecting surrounding adjacent points, the final average number k in the KNN algorithm, and the number m of APs.

3.2. Experiments

Our system's selection of various parameters is analyzed to achieve the best experimental results.

3.2.1. Accuracy of Different Numbers of Adjacent Points

In the experiment, we first determined the value range of adjacent points to be 2 to 5, and the experimental result is shown in Figure 1. When the number of adjacent points increases from 2 to 3, the positioning error is lower from 3.52m to 1.66m. When the number of adjacent points increases from 3 to 5, the positioning error will gradually increase to 3.11m. It can be seen that when the number of adjacent points is 3, the algorithm is effective.

3.2.2. Accuracy of Different k values

In the experiment, we measured the experimental results of k values, which are 1, 3, 5, 7, and 9. The experimental results are illustrated in Figure 2. If the value of k is from 1 to 3, the value of the positioning error decreases from 3.32m to 1.66m. When k increases from 3 to 9, the positioning error gradually increases to 3.18m, so the best experimental results are obtained when k is 3.

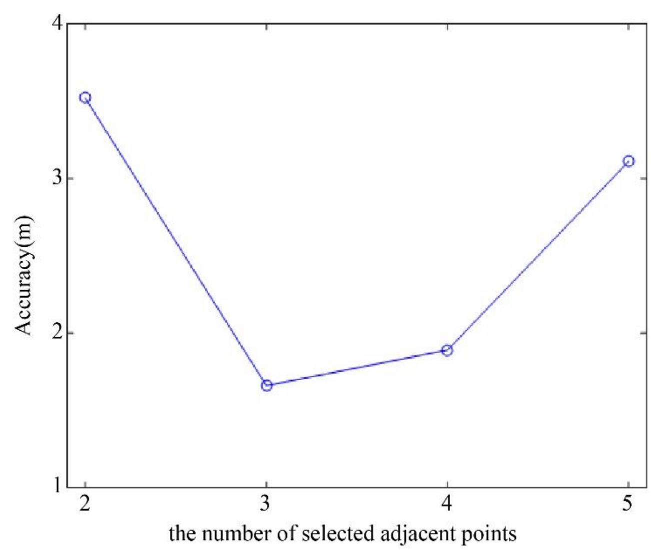

Fig. 1 Accuracy of different numbers of adjacent points

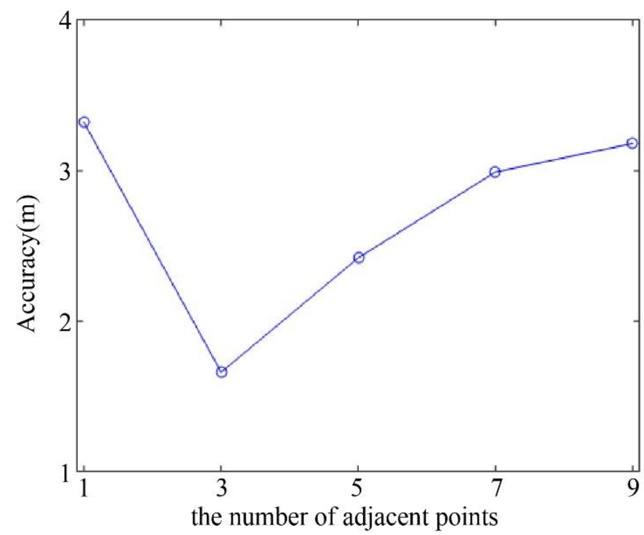

Fig. 2 Accuracy of different k values

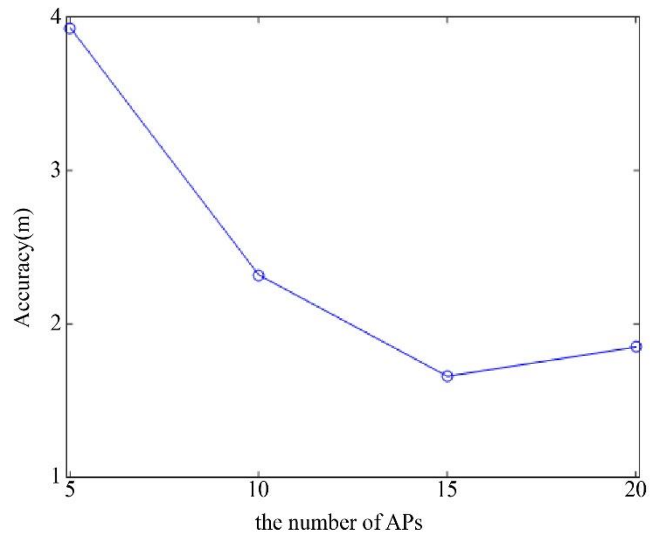

Fig. 3 Accuracy of the number of APs

3.2.3. Accuracy of the Number of APs

In the experiments, we cannot collect the signals of all APs in all locations, so we will have certain considerations when calculating the number of APs. We will label all APs on the map and select multiple APs with the best signals for calculation. The number of APs was 5, 15, and 20 when we experimented, respectively. The experimental results are shown in Figure 3. When the number of APs increases from 5 to 15, the positioning error drops from 3.93m to 1.66m. When it increases to 20, the positioning error will gradually increase to 1.85m and become stable. Considering the instability of the signal, we cannot collect 20 fingerprint information at any time, so our positioning system chooses the number of APs to be 15.

4. Conclusion

This paper proposes an effective localization system, Wi-SD. We first analyze defects of classical fingerprint positioning technologies, fingerprint spatial ambiguity, fingerprint time instability and difference of RSS observations of heterogeneous devices. In order to solve the defects, we design Wi-SD. According to our experiments, the signal level distribution fingerprint positioning algorithm has more accurate positioning accuracy.

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