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Fingerprint Indoor Localization Based on Improved WKNN

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Abstract

From mobile internet to the Internet of Things, location is a fundamental and indispensable information. People put forward an urgent need for accurate location information, and various location services also provide great convenience for people's daily life. As the outdoor positioning technology is quite mature, people focus on indoor positioning and propose a series of indoor positioning technologies and algorithms. Based on fingerprint localization, this paper proposes an indoor localization system based on the improved weighted K-Nearest neighbour (WKNN) algorithm. In the offline phase, we deploy Bluetooth access points (APs) and filter out APs with strong signals to reduce computing costs and improve localization accuracy. We process the AP signal data after screening and build a fingerprint database. In the online localization stage, we propose a WKNN algorithm based on weighted distance. This algorithm can effectively reduce the influence of signal fluctuations and improve the accuracy of online localization. At the same time, AP screening can effectively reduce the real-time localization time and improve localization efficiency. We collected a large amount of experimental data from the basement of the community near the school. Experiments show that our method can not only reduce computational complexity, but also effectively improve localization accuracy and improve real-time localization efficiency.

Keywords

Indoor Localization, WKNN, Wireless Network, Fingerprint Technology

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1. Introduction

With the rapid development of contemporary wireless communication technology, people's demand for location information services is also increasing. Location-based services have become a hot topic of discussion, digging out huge commercial value and scientific research potential. At the same time, it also raises new requirements and challenges for how to obtain more accurate location information. The classification of localization technology is mainly divided into outdoor wireless localization technology and indoor wireless localization technology. Outdoors, we obtain accurate location information through outdoor localization technologies such as global positioning system (GPS) [1] and Beidou [2] to realize car and personnel navigation. The increasing maturity of outdoor localization technology and products has also promoted the development of indoor localization technology. Indoor localization technology is playing an increasingly important role in various aspects of social production and life, such as route navigation, medical emergency, underground rescue, asset management, personnel tracking, and first-level emergency response for localization advertisements [3].

Indoor localization technology mainly includes ultra-wideband (UWB) indoor localization technology, radio frequency identification (RFID) indoor localization technology,

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ultrasonic indoor localization technology, infrared indoor localization technology, Zigbee indoor localization technology, WIFI indoor localization technology, Bluetooth indoor localization technology, etc. Each technology has its unique advantages and disadvantages. UWB indoor localization technology [4] has strong penetrating power, good anti-multipath effect, high security, high localization accuracy, but the cost is too high. RFID indoor localization technology [5] has high accuracy and low cost, but it does not have communication capabilities and has poor anti-interference capabilities. Ultrasonic indoor localization technology [6] has high overall accuracy, simple structure, but high cost and is affected by temperature. Infrared indoor localization technology [7] has high accuracy, but it cannot cross obstacles, and has high cost and high power consumption. Zigbee indoor localization technology [8] has low power consumption and low cost, but has low stability and is greatly affected by the environment. WIFI indoor localization technology [9] has low cost and high system accuracy, but it is easily affected by other signals. Bluetooth indoor localization technology [10] is similar to WIFI localization technology, but Bluetooth localization technology is easier to deploy and can support Android and iOS mobile devices.

Indoor localization algorithms mainly include three types: nearest neighbour method, triangulation method and fingerprint method. The nearest neighbour method is the simplest method. It directly selects the location of the AP with the highest signal strength, and the localization result is the location of the currently connected AP stored in the database. The triangulation method [11] obtains the distance or angle between the target and the AP through various parameters of the signal, and calculates the position with a geometric method. Including time of arrival method [12], relative time of arrival method [13], angle of arrival method [14], ranging methods based on signal strength, and so on. The fingerprint method [15] is to measure the signal characteristics at each position in advance and store it in the fingerprint database. When localization, match the current signal characteristics with those in the fingerprint library to determine the location.

Based on the Bluetooth indoor localization, this article uses the fingerprint method for localization operations. In the offline phase, Bluetooth APs are arranged, APs are screened, two characteristic attributes (mean and variance) are collected and processed, and a fingerprint database is constructed. In the online stage, based on the conventional WKNN algorithm, a method to improve the similarity calculation is proposed, that is, to improve the calculation of the distance between two points. Our main contributions are as follows:

1) By screening APs, while ensuring localization accuracy, we greatly reduce the calculation cost and improve the efficiency of real-time localization.
2) We use an improved WKNN algorithm, and the localization accuracy is about 2.33m.
3) Compared with the KNN algorithm and WKNN algorithm, our method has improved localization accuracy by 40.1% and 21.81% respectively.

2. Method

Our system is based on fingerprint localization system, including offline stage and online stage. The design of our system will be introduced in detail below.

2.1. Offline Phase

(1) Screen AP

Assume that N APs are deployed in an indoor environment, and M sampling points are planned. Sample AP signal values for a period of time at each sampling point, and average the collected signal values. The signal value of the AP sampled at the sampling point is $[rss_1^n, rss_2^n, \dots, rss_z^n]$, where n represents the nth AP, and z represents the collected sample volume.

Due to the influence of complex environments such as wall partitions, personnel flow, and co-frequency interference in the indoor environment, the received signal strength (RSS) collected at the sampling points will fluctuate to a certain extent. Compared with APs with weak signals, APs with strong signals have higher signal stability. In order to improve the accuracy of the signal value and reduce the calculation cost, APs are screened, and APs with high signal strength are retained. The sampling point (x_i, y_i) takes the average of the measured AP signal value and records it as $RSS_i = [RSS_i^1, RSS_i^2, \dots, RSS_i^n, \dots, RSS_i^N]$, where the formula for calculating the signal average is:

$$RSS_i^n = \frac{1}{z}\sum_{j=1}^{z} rss_j^n \quad (1)$$

where $1 \le i \le M$. For each AP, calculate the sum of its collected signal values at all sampling points. The formula is as follows:

$$Sum_p = \sum_{j=1}^{M} RSS_j^p \quad (2)$$

where $1 \le p \le N$. The sum of the signal values of N APs is obtained, and the AP with the highest α% of the sum of signal values is selected as the attribute AP.

(2) Build fingerprint database

Assuming that there are s APs selected, the signal values of the s APs are collected at the sampling point and processed to construct a fingerprint database. In the AP screening stage, the average signal value of each sampling point is calculated according to the AP signal value of a period of time sampled as a part of the fingerprint. Since the average value cannot reflect the amplitude and fluctuation of the signal, the variance attribute is added as another part of the fingerprint. Calculate the variance of the signal value of each AP at each sampling point. The fingerprint of the variance is recorded as $\sigma_i = [\sigma_i^1, \sigma_i^2, \ldots, \sigma_i^n, \ldots, \sigma_i^s]$, Where σ_i^n represents the variance of the signal value of the nth AP collected on the ith sampling point. The calculation formula of variance σ_i^n is expressed as:

$$\sigma_i^n = \frac{1}{z}\sum_{j=1}^{z}(rss_j^n - RSS_i^n)^2 \tag{3}$$

For the sampling point (x_i, y_i), take (RSS_i, σ_i) as the fingerprint of the point. In this way, a fingerprint database is constructed.

2.2. Online Phase

Traditional fingerprint localization technology uses the KNN algorithm or WKNN algorithm to locate the target directly in the online phase after collecting RSS signals in the offline phase. Compared with the KNN algorithm, the traditional WKNN algorithm increases the weight attribute of the nearest point with higher accuracy. However, both KNN and WKNN just directly use the Euclidean distance of the signal value as the criterion for the similarity between points. Ideally, the closer the physical location is, the smaller the Euclidean distance between RSS and the higher the similarity. However, in actual situations, the difference in signal strength may not be completely caused by the distance of the physical location, but may also be caused by the fluctuation of the signal strength itself, so that the Euclidean distance does not truly reflect the actual physical distance. Therefore, we propose an improved method for the shortcomings of Euclidean distance. For the square of the difference between each AP signal, we give it a weight based on variance.

Specifically, the set point is (x, y), and the RSS signal value sampled at this point is $[RSS_1, RSS_2, \ldots, RSS_s]$. The similarity between the localization point (x, y) and the sampling point (x_i, y_i) is expressed by the distance d_i:

$$d_i = \sqrt{\sum_{n=1}^{s}[\omega_i^n (RSS_n - RSS_i^n)^2]} \tag{4}$$

The weight ω_i^n is represented by the reciprocal of the variance of each AP signal at each sampling point, and the reciprocal of the variance is normalized. The calculation formula of the weight ω_i^n is as follows:

$$\omega_i^n = \frac{\frac{1}{\sigma_i^n}}{\sum_{p=1}^{s}\frac{1}{\sigma_i^p}} \tag{5}$$

where $1 \le n \le s$.

The variance reflects the discrete degree of AP signal value measured at the sampling point. The greater the variance, the greater the fluctuation of the RSS signal, that is, the higher the probability that the sampled RSS signal value and the mean value are different. In order to reduce the influence of signal fluctuations, the reciprocal of the variance is normalized and added as a weight coefficient to the distance calculation to improve the localization accuracy.

After obtaining the distance sequence $[d_1, d_2, \ldots, d_M]$, select k points with the smallest distance as the base point of the localization target. Suppose the sequence composed of k minimum distances is $[d_1, d_2, \ldots, d_k]$. The distance represents the similarity, the smaller the distance, the higher the similarity. We set a weight φ based on the reciprocal of the distance, and normalize the reciprocal of the distance. The distance indicates the similarity of two points. The smaller the distance, the higher the similarity, that is, the closer to this sampling point, the greater the weight. The calculation formula of the base point weight is as follows:

$$\varphi_j = \frac{\frac{1}{d_j+1}}{\sum_{i=1}^{k}\frac{1}{d_i+1}} \tag{6}$$

where $1 \le j \le k$. The distance plus one is to avoid the situation where the denominator is zero. Finally, the target localization point (x, y) is calculated based on similar sampling points and weights:

$$(x, y) = \sum_{j=1}^{k}[\varphi_j(x_j, y_j)] \tag{7}$$

3. Experiment and Analysis

3.1. Experiment Environment

Our experimental environment selected an empty underground garage near the school. We selected an area of about 500 square meters in the garage to plan sampling points and deploy Bluetooth APs. We planned 18×29 sampling points in the area, totaling 522. We deployed 50 APs on the walls and pillars of the garage. We collect RSS data for one minute at each sampling point.

3.2. Analysis of the Experimental Results

First, we average the collected RSS values of the original APs, and select APs with larger signal strength. We set $\alpha = 20$, that is, select the top 20% APs (10 APs) with the largest signal strength as the attribute AP we want to use. By screening APs, we have greatly reduced the calculation cost, not only improved the localization accuracy, but also improved the real-time localization efficiency in the localization phase. Then we calculate the variance of the original RSS values of these 10 APs, and use the mean and variance together as the fingerprint attributes of the sampling points to build a fingerprint database.

From Figure 1, we can see that the WKNN algorithm is obviously better than the KNN algorithm, and our improved WKNN algorithm is generally better than the WKNN algorithm. In the end, the localization error accuracy of our improved WKNN algorithm is 2.33m, which is 40.1% and 21.81% higher than the KNN algorithm and WKNN algorithm, respectively.

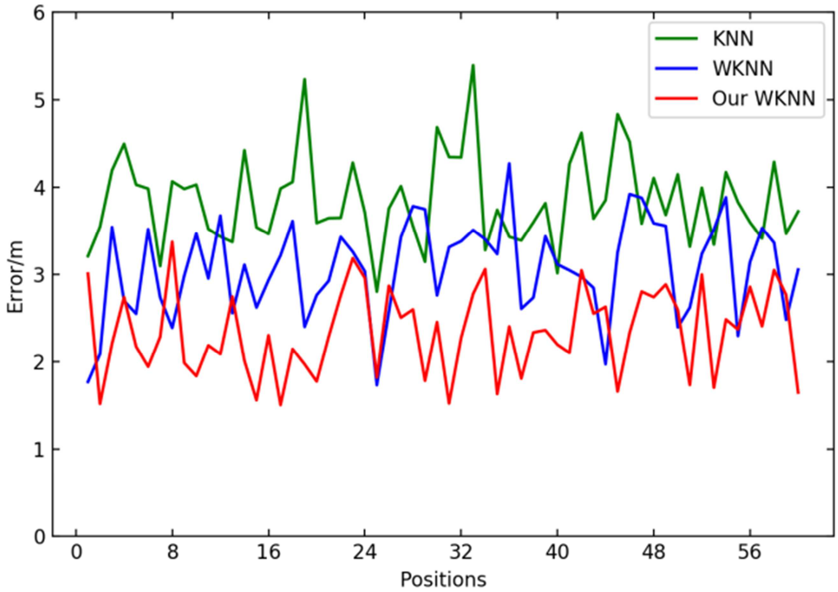

Figure 1. Method comparison.

4. Conclusion

Among the many indoor localization algorithms, the most commonly used algorithm is the fingerprint method. The fingerprint method is characterized by sampling first and then localization. Based on the fingerprint method, this paper proposes an improved WKNN algorithm for localization. In the offline phase, we screen the APs without affecting the accuracy of the calculation cost. By screening the AP with the strongest signal value, the accuracy of the signal value is improved, the dimensionality of the fingerprint signal is reduced, the amount of calculation is reduced, and the efficiency of real-time localization is also improved. Due to the fluctuation of the signal, the Euclidean distance between the signal values does not completely represent the physical distance. We calculate the variance of the signal value of each AP selected at each sampling point, and then use the weight based on the variance to improve the distance, reducing the impact of signal fluctuations. In the online localization stage, calculate the distance between the RSS value of the test point and the RSS value of the sampling point. The 5 sampling points with the smallest distance are selected as the base points of the test prediction points, and the coordinates of the final prediction points are calculated. Our experimental results show that our method has achieved good results: low computational cost, small error accuracy, and high localization efficiency.

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