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An Indoor Localization Method Based on Fuzzy Localization

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Abstract

In recent years, people are increasingly pursuing convenient and networked lifestyles. Therefore, the demand for accurate indoor positioning services is growing continuously. And indoor positioning technology has already become a research hotspot of scholars at home and abroad. Due to the lack of satellite signals in the indoor environment, such as GPS, Beidou and other satellite navigation systems can not be used, indoor positioning needs to find other ways. Meanwhile, with the rapid development and application of Internet of Things technology, numerous indoor positioning methods have emerged. Among these methods, the positioning method based on wireless local area network (WLAN) is one of the more commonly used methods due to the wide coverage of wireless infrastructure and the advantages of simple deployment, low cost and high universality of WiFi. Aiming at the problem that the received signal strength of indoor WiFi is easily affected by indoor environment and multipath effect, thus the connection between location fingerprint and real location is inevitably affected, this paper proposes an improved algorithm based on fuzzy location. This paper focuses on the construction of fingerprint database and fingerprint matching for WiFi fingerprint positioning, summarizes the key technologies of existing WiFi fingerprint positioning, analyzes the challenges in WiFi fingerprint positioning such as the spatial ambiguity and temporal instability of Received Signal Strength (RSS). On this basis, the improved algorithm is tested, and the results show that the algorithm improves the positioning accuracy to a certain extent.

Keywords

Indoor Localization, Location Fingerprint, Received Signal Strength, Fuzzy Localization

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1. Introduction

Nowadays, with the widespread popularity of mobile smart devices and the rapid development of the Internet of Things, people's demand for location-based services is also increasing. The fast-response, reliable and widespread positioning technology enables users/mobile objects to obtain the current location in real time, which is the prerequisite basis for location-aware and service applications.

In outdoor positioning, the commonly used positioning systems are basically realized by satellites, with various enhancement techniques, the positioning accuracy can reach sub-meter level in outdoor open areas [1], such as the Global Positioning System (GPS) and the Beidou Navigation System (BDS). However, most of human activities are carried out indoors and indoor location information is crucial to daily life [2]. So it stimulates people's desire to obtain accurate location anytime and anywhere in the indoor environment. Whereas, the satellite signals will be blocked and interrupted in an indoor environment. Therefore, these positioning systems are not suitable for indoor environments [3].

This has also led to the lack of a perfect solution in the field of

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indoor positioning. In the past few decades, many indoor positioning technologies, such as WIFI, RFID, UWB, sound signals, magnetic signals and inertial sensors, have gradually developed as the mainstream [4-11]. But each of these technologies has its own advantages and disadvantages. In order to meet the positioning requirements of a certain level of accuracy, most indoor positioning technologies require the deployment of additional dedicated hardware facilities. The positioning cost is high, and positioning accuracy and coverage are limited by hardware conditions, which are not conducive to application and promotion. However, the positioning technology based on WiFi can rely on WLAN infrastructure, with the popularization of WiFi Access Points (AP) and smart terminals, thus without additional special equipment, just positioning software can realize the positioning of mobile intelligent terminals. Therefore, this positioning technology is very attractive among all indoor positioning technologies due to its low positioning cost and its ability to meet the positioning accuracy requirements of most indoor applications.

Nevertheless, this method still has its own shortcomings. The main one is that the RSS of WiFi signal is uncertain, which is an important factor affecting the positioning accuracy of RSS positioning. The uncertainty is mainly reflected in the following three aspects: (1) Spatial ambiguity: RSS at different locations may be similar, resulting in similar RSS values even at different locations; (2) Temporal instability: RSSs at a specific location may change over time, resulting in different RSS values even at the same location [12]; (3) Device heterogeneity: The RSS values measured by different devices at the same location and at the same time may be different, resulting in different RSSs results on different devices [13].

Taking WiFi indoor positioning technology as an example, it can basically be summarized into two types of algorithms: ranging-based localization and fingerprint-based localization. The basic principle of the ranging-based localization algorithm is that the energy attenuation of the line signal in the propagation process and the propagation distance conform to a certain theoretical model, so the signal propagation distances can be inversely deduced according to the RSS values. At present, the log-distance path loss model (LDPL) is widely used. However, in a complex real environment, the dynamic characteristics of signal propagation and the instability of the environment usually produce large errors in the calculation of signal propagation distance, which makes it difficult for the ranging-based localization technology to achieve a high accuracy. On the other hand, the non-ranging localization algorithm mainly takes advantage of the spatial difference of the wireless signals in different positions, and takes the wireless signals as the physical location features, namely 'fingerprints'. And the corresponding positioning method is called fingerprint-based localization. Fingerprint-based localization builds a fingerprint database to store the location-fingerprint relationships, and realizes the estimation of the user's location by means of fingerprint feature recognition and matching [14].

This paper mainly adopts the fingerprint-based localization technology based on WiFi, and the next chapter mainly introduces its related basic content.

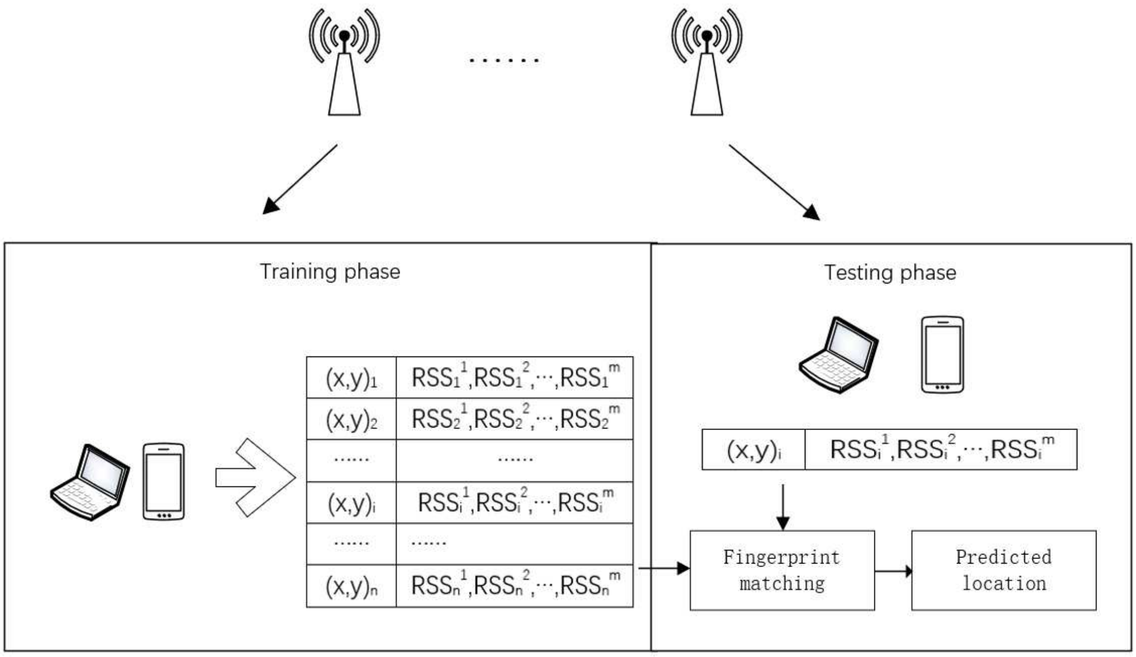

Figure 1. WiFi fingerprint positioning process.

2. Related Technologies

2.1. WiFi Fingerprint Technology Positioning Process

WiFi fingerprint positioning methods usually include two phases: training phase/offline phase and testing/online phase. In the training phase, select appropriate location sampling points according to the spatial layout of the positioning area to ensure that sufficient fingerprint information is provided in the positioning phase, and then collect the RSS values of different APs in the area at each sampling point, and use these RSS values as Fingerprint data, and store it in the fingerprint database in a one-to-one correspondence with the corresponding location. Generally speaking, at the time of collection, multiple RSS values are measured at each collection point and their average value is taken as the fingerprint of that point and stored in the database, thereby reducing the environmental impact.

Specifically, suppose the location area is artificially specified as a discrete location interval Area= $\{A_1, A_2, A_3, \ldots, A_n\}$, where n is the number of sampling points in the location area, where the location of Ai The coordinates are (x_i, y_i), and the corresponding RSS fingerprint is expressed as $RSS_i = \{r_{i1}, r_{i2}, r_{i3}, \ldots\ldots, r_{im}\}$, where m is the number of APs in the acquisition area, and r_{ij} is the measured value at position Ai RSS value of the j-th AP ($1 \le j \le m$). All fingerprints finally form a complete fingerprint map F= $\{f_1, f_2, f_3, \ldots, f_n\}$ composed of $<A_i, RSS_i>$.

In the testing phase, the user requests his/her current position by sending the real-time RSS values of his/her location to the server as the query credential. The server matches the query credential with all the data in the fingerprint database according to the specific matching algorithm, and returns the position corresponding to the closest fingerprint as the user's position estimation.

However, in actual situations, because of the instability of RSS, it usually takes a lot of time and manpower to collect fingerprint data. Once the indoor environment changes, it may cause the fingerprint of the fingerprint database to become invalid. Therefore, we need to constantly Update the fingerprint information of the database to ensure the closeness of the association between the fingerprint and the location.

2.2. k-Nearest Neighbor Algorithm

The k-Nearest Neighbor (KNN) algorithm is a classic machine learning algorithm. After we get the fingerprint database in the offline stage, the user sends the RSS value of his location to the server, and the server compares the fingerprint with the fingerprint in the database one by one to find out the similarity degree between the current user's location and the fingerprint of each sampling point. The similarity degree is generally calculated by Euclidean distance [15].

Assuming that the RSS value of each sampling point in the fingerprint database can be expressed as $R_i=(r_1^i, r_2^i, r_3^i, \ldots, r_m^i)$, where m is the number of APs measured, and the RSS measured at the location of the user during the test The value can be expressed as $P=(p_1, p_2, p_3, \ldots, p_m)$. Then the similarity between the user's location and the RSS of each sampling point in the database can be expressed as follows:

$$dist(P, R_i) = \sqrt{\sum_{j=1}^{n} \left(p_j - r_j^i\right)^2} \quad (1)$$

In the KNN algorithm, the value of K is not fixed, and the value of K needs to be determined according to the actual situation. In this article, we take K as 5. After determining k to take 5, we finally keep the coordinates of the 5 sampling points closest to the fingerprint of the user's current position in the fingerprint database, and the new coordinates obtained on average are the final KNN algorithm predicted coordinates.

The weight k-Nearest Neighbor (WKNN) algorithm introduces the idea of weight on the basis of the KNN algorithm [16]. Based on the above formula, the weight factors of the first k nearest neighbor points are as follows:

$$(x, y) = \frac{\sum_{i=1}^{K} \frac{1}{d_i}(x_i,\ y_i)}{\sum_{i=1}^{K} \frac{1}{d_i}} \quad (2)$$

3. Improved Fingerprint Location Algorithm

Generally speaking, in the online phase, we will match the RSS fingerprint sent by the user's current location with the entire fingerprint database. If the nearest neighbor is selected incorrectly, the final positioning result will be very unsatisfactory. Therefore, for this situation, we first divide the entire positioning area into n small areas in the offline phase, and then determine the approximate area of the user's location in the online phase. In other words, first perform Fuzzy positioning is performed once, and it is determined in a smaller area, and then accurate positioning is performed in this smaller area to obtain the predicted coordinates. In this way, the neighboring points of the predicted point are restricted to a smaller range, which ensures that the positioning results will not have large errors, making the algorithm more robust.

Specifically, we divide the entire sampling area into n blocks, the position range that can be represented is $A=\{a_1, a_2, \ldots, a_n\}$, and measure some fingerprint data in each block, and use these fingerprint data as The characteristic fingerprint of this area, such as: the fingerprint data of the i-th block area can be expressed as:

$$a_i = \begin{bmatrix} p_0^1 & p_0^2 & \cdots & p_0^m \\ p_1^1 & p_1^2 & \cdots & p_1^m \\ \vdots & \vdots & & \vdots \\ p_n^1 & p_n^2 & \cdots & p_n^m \end{bmatrix} \tag{3}$$

Where n is the number of sampling points in the i-th block region, and m is the number of AP.

In the testing phase, when the user sends back the current position fingerprint, the classification algorithm is used to divide it into the nearest small area, and then the WKNN algorithm is used to locate it, and the final prediction coordinate is obtained.

4. Experiment

This experiment mainly environment is the size of 12m×6m around the office, and in which placed 10 AP, used the two phones (HUAWEI Nova4 and Honor V20) and glory on the sampling, the sampling density of 1m×1m, and 5 minutes at each sampling point sampling, collecting 30 times per minute, the collected data using the average filtering method for noise reduction.

The specific plan of the experimental environment is as follows:

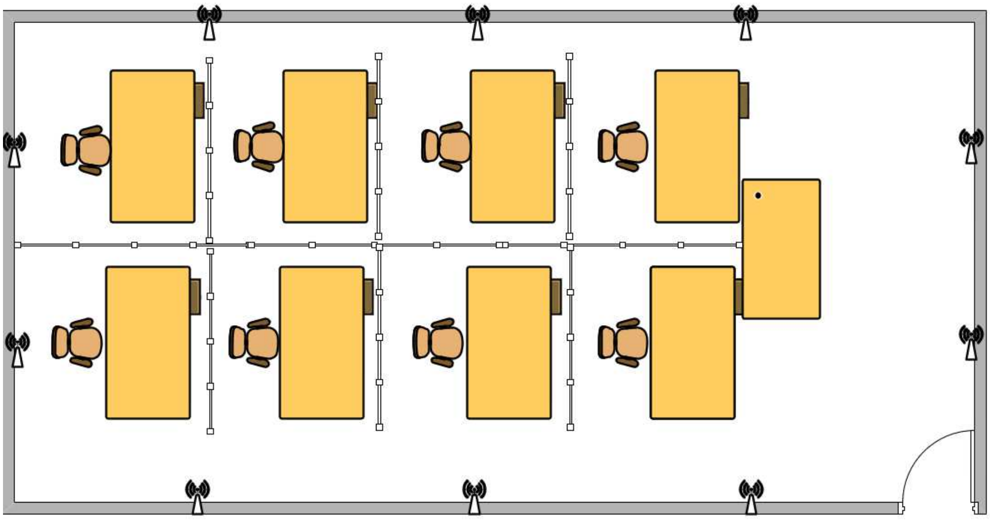

Figure 2. Office floor plan.

In order to verify the effectiveness and feasibility of the improved positioning method proposed in this paper, this improved algorithm is compared with KNN algorithm according to the above method and environment, and the results are compared as shown in the figure below:

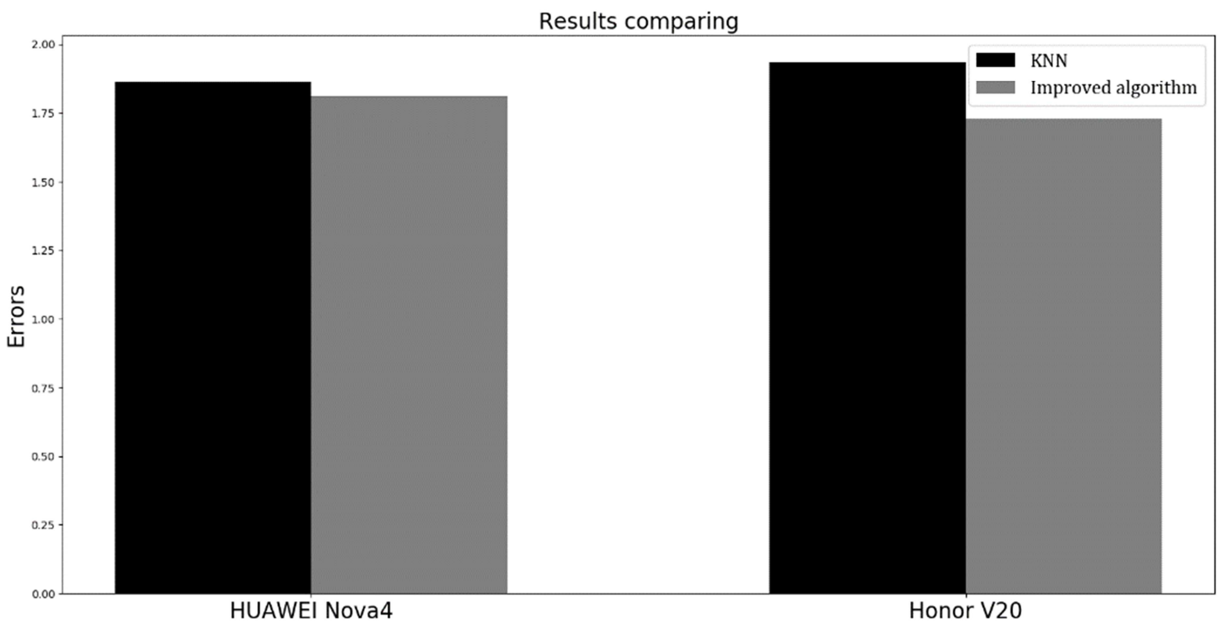

Figure 3. Comparison of experimental results.

5. Conclusions

This paper proposes an improved indoor positioning algorithm based on KNN algorithm. It mainly carries out a fuzzy positioning before precise positioning, determines a rough range, and controls the positioning error within a small range, making the algorithm more robust. Experimental results show that this method optimizes the location algorithm and reduces the location error to some extent.

References

[1] KAPLAN E D, HEGARTY C J. Understanding GPS, Principles and Applications [M]. 2nd ed. Boston: Artech House, 2006.

[2] WEISER M. The Computer for the 21st Century [J]. Scientific American, 1991, 265 (3): 94-104.

[3] F. L. Piccolo, “A new cooperative localization method for UMTS cellular networks,” in Proc. IEEE Glob. Telecommun. Conf., New Orleans, LA, USA, Nov./Dec. 2008, pp. 1–5.

[4] F. Ijaz, H. K. Yang, A. W. Ahmad, and C. Lee, “Indoor positioning: A review of indoor ultrasonic positioning systems,” in Proc. IEEE 15th Int. Conf. Adv. Commun. Technol. (ICACT), Rajampet, India, 2013, pp. 1146–1150.

[5] H. Koyuncu and S. H. Yang, “A survey of indoor positioning and object locating systems,” IJCSNS Int. J. Comput. Sci. Netw. Security, vol. 10, no. 5, pp. 121–128, 2010.

[6] Z. Farid, R. Nordin, and M. Ismail, “Recent advances in wireless indoor localization techniques and system,” J. Comput. Netw. Commun., vol. 2013, 2013, Art. no. 185138, doi: 10.1155/2013/185138.

[7] H. Liu, H. Darabi, P. Banerjee, and J. Liu, “Survey of wireless indoor positioning techniques and systems,” IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 37, no. 6, pp. 1067–1080, Nov. 2007.

[8] Y. Gu, A. Lo, and I. Niemegeers, “A survey of indoor positioning systems for wireless personal networks,” IEEE Commun. Surveys Tuts., vol. 11, no. 1, pp. 13–32, 1st Quart., 2009.

[9] A. D. M, “A comparative analysis on indoor positioning techniques and systems,” Int. J. Eng. Res. Appl., vol. 3, no. 2, pp. 1790–1796, 2013.

[10] M. A. Al-Ammar et al., “Comparative survey of indoor positioning technologies, techniques, and algorithms,” in Proc. Int. Conf. Cyberworlds (CW), Santander, Spain, Oct. 2014, pp. 245–252.

[11] Q. D. Vo and P. De, “A survey of fingerprint-based outdoor localization,” IEEE Commun. Surveys Tuts., vol. 18, no. 1, pp. 491–506, 1st Quart., 2016.

[12] Alikhani N, Moghtadaiee V, Ghorashi S A. Fingerprinting Based Indoor Localization Considering the Dynamic Nature of Wi-Fi Signals [J]. Wireless Personal Communications, 2020, 115 (1): 1-20.

[13] Wu C, Xu J, Yang Z, et al. Gain Without Pain: Accurate WiFi-based Localization using Fingerprint Spatial Gradient [J]. Proceedings of the ACM on Interactive Mobile Wearable and Ubiquitous Technologies, 2017, 1 (2): 1-19.

[14] Le Dortz, Nicolas, F. Gain, and P. Zetterberg. "WiFi fingerprint indoor positioning system using probability distribution comparison." IEEE International Conference on Acoustics IEEE, 2012: 2301-2304.

[15] Sun, Yongliang, et al. "KNN-FCM hybrid algorithm for indoor location in WLAN." 2009 2nd International Conference on Power Electronics and Intelligent Transportation System (PEITS) IEEE, 2010.

[16] Wu, Di, Y. Xu, and L. Ma. "Research on RSS based Indoor Location Method." Pacific-asia Conference on Knowledge Engineering & Software Engineering IEEE Computer Society, 2009.