Physics Journal
Vol. 7, No. 1, 2021, pp. 1-4
http://www.aiscience.org/journal/pj
ISSN: 2471-8483 (Print); ISSN: 2471-8491 (Online)

Improved Algorithm of WiFi Fingerprint Location Based on Signal Strength

Yonghao Zhao[1, 2, *]

[1]School of Computer Science and Technology, Nanjing University of Technology, Nanjing, China
[2]School of Information Engineering, Yancheng Teachers University, Yancheng, China

Abstract

With the development of information technology, the basic improvement of network infrastructure and the rapid development of mobile network, the development direction of the world economy and people's thinking and way of life have undergone tremendous changes due to the rapid development of wireless technology. Nowadays, people's demand for location services is increasing. Compared with outdoor GPS navigation systems, indoor positioning technology still has a long way to go. Indoor positioning is a hot issue in navigation technology. In recent years, many indoor positioning technologies have been proposed. And location fingerprint positioning is a commonly used technology. Among them, the positioning algorithm using KNN is the most classic positioning method. Due to the complexity of the environment, the concept of weight is introduced on the basis of the KNN algorithm, which alleviates the impact of different environments to a certain extent. This paper proposes a new and improved algorithm based on the KNN algorithm. In order to fully consider the complexity of the environment, the fingerprint data is preprocessed to eliminate the interference of abnormal signal values firstly, and then a new weight method is introduced to weight the KNN algorithm. The experimental results show that this method can further improve the positioning accuracy.

Keywords

Indoor Positioning, Location Fingerprint, KNN Algorithm, Improved Weighting

Received: March 3, 2021 / Accepted: March 26, 2021 / Published online: April 16, 2021

1. Introduction

With the development of radio communication technology and mobile Internet technology, the intelligent level of mobile terminals continues to improve. Location-based services are gradually becoming the daily needs of all walks of life and real life. Users also put forward higher requirements for indoor positioning technology. Different from the outdoor positioning satellite navigation system, due to the barrier of reinforced concrete, it is useless in the indoor environment [1, 2]. At the same time, due to the complex indoor space structure and the obstruction of various office facilities and personnel, the positioning accuracy of various positioning systems based on radio signals in the indoor environment is deteriorated.

In the past few decades, many indoor positioning technologies based on WiFi, Radio Frequency Identification (RFID), Ultra Wide Band (UWB), ultrasonic, infrared, geomagnetic signals, and inertial sensors have gradually developed as the mainstream [3-8]. However, these technologies have their own limitations. RFID system deployment is complicated, the application range is narrow and easy to be affected by the environment. The coverage of UWB is too small, the positioning cost is high, and the smart terminal does not support this technology temporarily. Ultrasound Positioning technology is susceptible to multipath effects and non-line-of-sight propagation. At the same time, it also requires a lot of underlying hardware facilities, and the overall

* Corresponding author
E-mail address: classforyc@163.com

cost is relatively high. In infrared positioning technology, because light cannot pass through obstacles, infrared rays can only travel through the line of sight, which is easily interfered by other lights, and the transmission distance of infrared is also short. Geomagnetic positioning technology is susceptible to interference from constantly changing electrical and magnetic signal sources in the environment. Therefore, in comparison, WiFi positioning technology is undoubtedly the simplest, fastest, most convenient and economical indoor positioning technology. Because it does not require additional professional equipment and has a wide coverage.

The current indoor positioning technology mainly includes trilateral measurement [9], triangulation [10] and signal strength measurement [11]. Among them, trilateral measurement uses known distances to calculate the position of an object from at least three fixed points in two-dimensional space or four fixed points in three-dimensional space. Triangulation relies on the known distance between two measuring devices and the measurement angle from these two points to the object. The signal strength measurement is to compare the measured signal strength with the established signal strength fingerprint database. Taking into account the problems of non-line-of-sight and multipath transmission caused by the complexity of the indoor environment, the measurement time and measurement angle will have large deviations, so most of the indoor WiFi positioning technologies adopt the most simple and feasible location algorithm based on signal strength measurement.

However, the positioning technology based on WiFi signal strength still has the problem of poor positioning. Therefore, in this paper, the traditional positioning technology based on WiFi signal strength has been improved to a certain extent, which greatly improves the positioning accuracy.

2. Fingerprint Positioning Technology

Fingerprint positioning technology needs to collect the received signal strength (RSS) at each sampling point. Because wireless signals have spatial differences in different positions, the signal strength at each position is different. And we take them called ‘fingerprints’. We realize the final positioning according to the correspondence between the ‘fingerprint’ and the physical address at each location [12, 13]. Generally speaking, fingerprint positioning technology includes two stages, namely the offline data collection stage and the online real-time positioning stage.

The specific fingerprint positioning process is shown in Figure 1.

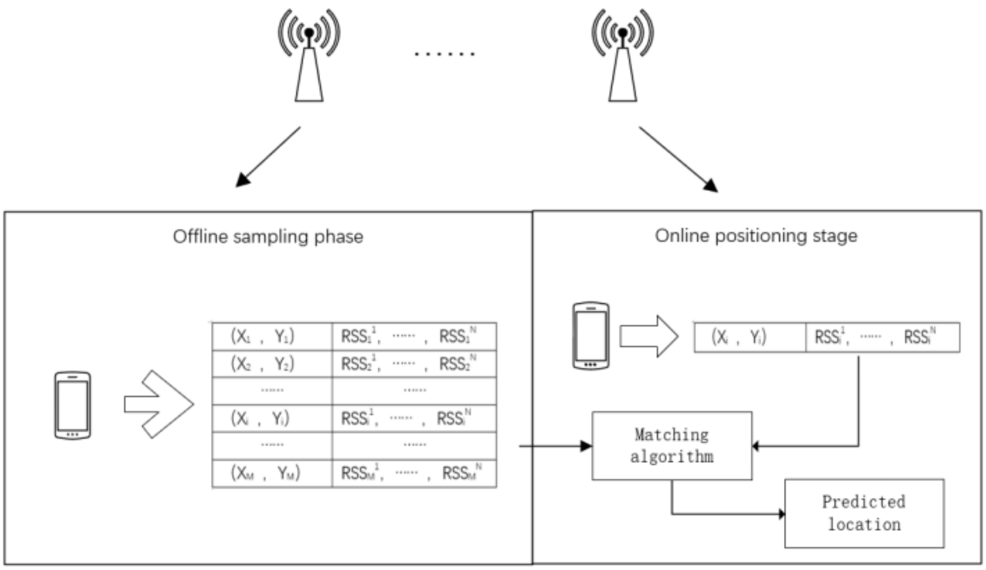

Figure 1. Fingerprint positioning flow chart.

Offline sampling stage

In the offline sampling stage, it is necessary to randomly place wireless base stations in the area and record the position coordinates, then divide the area into multiple virtual network spaces, set the grid nodes as the alignment coordinates of the sampling points, measure them and record the data. In order to ensure that all sampling points can receive the signal from the base station, an information receiving device is placed at each sampling point, then the received RSS value and position coordinate data are recorded in the fingerprint database. Finally, after collecting enough data, a complete fingerprint database can be built.

Assuming that there are M sampling locations and N access point (AP) signals in the sampling interval D. And the RSS value of the nth AP measured at the m-th sampling location can be expressed as RSS_m^n. Therefore, the fingerprint database finally sampled can be expressed as

$$RSS_{M*N} = \begin{bmatrix} RSS_1^1 & \cdots & RSS_1^N \\ \vdots & \ddots & \vdots \\ RSS_M^1 & \cdots & RSS_M^N \end{bmatrix} \quad (1)$$

Online positioning stage

In the online positioning stage, it is necessary to compare the RSS data of the point to be measured with the data in the fingerprint database through a matching algorithm to obtain the predicted coordinates. The most classic algorithm is the K nearest neighbour (KNN) algorithm, which determines the K nearest neighbours with the highest similarity by calculating the similarity of the two corresponding vectors. In this paper, the Euclidean distance [14] is used to find the similarity between the two sets of RSS values. Therefore, we can use equation (2) to find the similarity between the RSS value of the point to be measured and all the sampling points in the fingerprint database. And get the most similar K sampling points, these points are the nearest neighbour points. Then the coordinates of these nearest neighbours are averaged and output, and this output is the final predicted coordinates.

$$dist = \sqrt{\sum_{n=1}^{m} (p_n - r_n^i)^2} \quad (2)$$

Where, p_n is the RSS value of the nth AP measured on the point to be measured, and r_n^i represents the RSS value of the nth AP measured at the i-th point in the K nearest neighbours. In this paper, K is 5.

3. Algorithm Improvement

This paper improves the traditional fingerprint location algorithm, which can be divided into two points: (1) Improve the fingerprint database, filter the undetected or weak APs in the original RSS data and store them in the fingerprint database; (2) Improve the matching algorithm, in order to further distinguish the fingerprints at each location, the KNN algorithm in the traditional matching algorithm has been optimized to a certain extent.

For the fingerprint database, in the actual measurement process, we found that the signal of each AP is unstable, and the signal value at some of the sampling points is too weak or even not measured, which affects the positioning accuracy. Therefore, in order to eliminate these effects, we set a threshold to judge the RSS. When it is lower than the threshold, the signal strength is considered to be too low, which will have a negative impact on the positioning result. Then we set the RSS value of all APs where no signal is detected and the RSS value below the threshold as the threshold to eliminate their negative impact on the positioning results. The threshold in this paper is -91.

In the positioning phase, the KNN algorithm cannot meet the daily requirements for positioning accuracy. Therefore, the weighted K nearest neighbour (WKNN) algorithm is used more often [15]. The WKNN algorithm introduces the concept of weight. On the basis of the formula (2), the final predicted coordinates are obtained through formula (3).

$$(x, y) = \frac{\sum_{i=1}^{K} \frac{1}{dist_i}(x_i, y_i)}{\sum_{i=1}^{K} \frac{1}{dist_i}} \quad (3)$$

In this paper, the weights of the WKNN algorithm are improved, and the final predicted coordinates are obtained by formula (4).

$$(x, y) = \frac{\sum_{i=1}^{K} \frac{1}{e^{dist_{i+1}}}(x_i, y_i)}{\sum_{i=1}^{K} \frac{1}{e^{dist_{i+1}}}} \quad (4)$$

4. Experiment

This paper mainly conducts experiments in a garage made up of two rectangles. The sizes of the two rectangles are 11m×22m and 10m×32m respectively. The entire sampling map is about 562 square meters. Among them, there are 14 AP points and 605 sampling points. At the same time, we used two mobile phones (Honor V20, Huawei Nova4) for sampling. Each sampling point was sampled for 5 minutes, 30 times per minute, and the collected data was denoised by means of mean filtering.

The specific garage floor plan is shown in Figure 2.

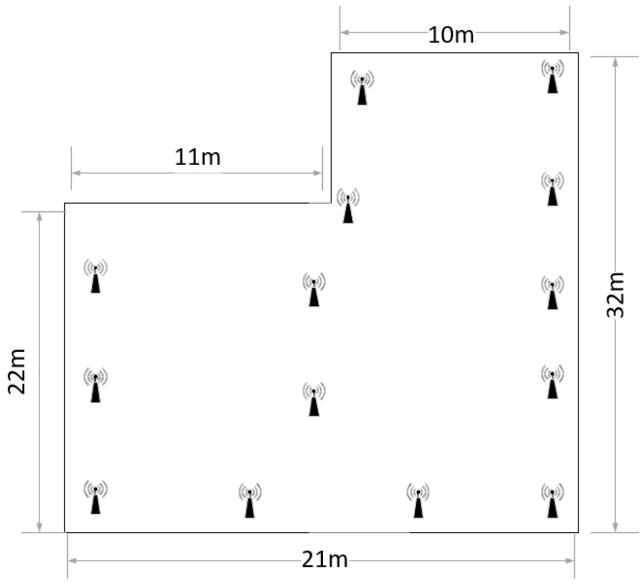

Figure 2. Garage plan.

In order to verify the effectiveness and feasibility of the improved positioning method proposed in this paper, according to the above method and environment, we compare the improved algorithm with the KNN algorithm. The results obtained are compared as shown in Figure 3.

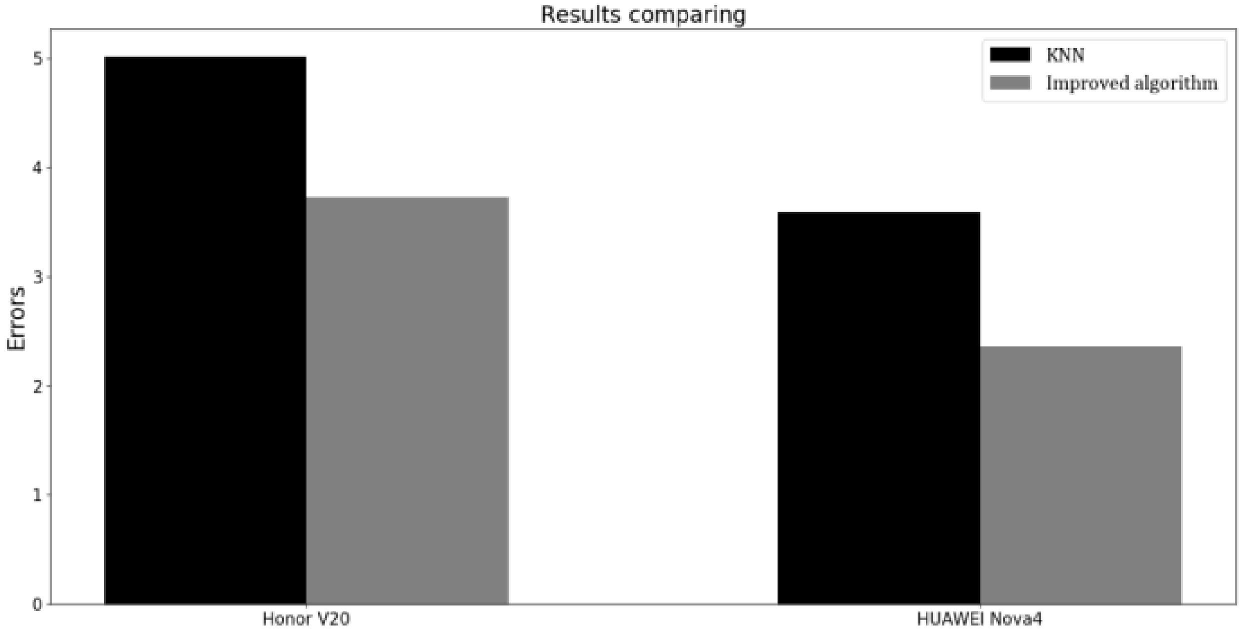

Figure 3. Comparison of experimental results.

The positioning errors of the KNN algorithm are 5.02 meters and 3.59 meters respectively, while the positioning errors of the improved algorithm are 3.73 and 2.36 respectively, and the accuracy is increased by 25.7% and 34.3% respectively.

5. Conclusions

This paper optimizes the traditional fingerprint positioning technology. Not only is the threshold value set to remove the RSS value that affects the positioning accuracy in the process of establishing the fingerprint map, but also certain improvements are made in the positioning phase. Experiments show that this method optimizes the positioning algorithm to a certain extent and reduces the positioning error.

References

[1] Motte H, Wyffels J, Strycker L D, et al. Evaluating GPS Data in Indoor Environments [J]. Advances in Electrical and Computer Engineering, 2011, 11 (3): 25-28.

[2] Xiaoming L, Xinglong T, Changsheng Z. PSO-LSSVR Assisted GPS/INS Positioning in Occlusion Region [J]. Sensors (Basel, Switzerland), 2019, 19 (23).

[3] W. Sakpere, M. Adeyeye Oshin and N. B. Mlitwa, "A State-of-the-Art Survey of Indoor Positioning and Navigation Systems and Technologies", South African Comput. J., vol. 29, no. 3, pp. 145197, 2017.

[4] Zafari F, Gkelias A, Leung K K. A Survey of Indoor Localization Systems and Technologies [J]. Communications Surveys & Tutorials, IEEE, 2019.

[5] Evolution of Indoor Positioning Technologies: A Survey [J]. Journal of Sensors, 2017.

[6] 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.

[7] 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.

[8] 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.

[9] Niculescu, D. Positioning in ad hoc sensor networks [J]. Network IEEE, 2004, 18 (4): 24-29.

[10] Ma Y, Wang B, Pei S, et al. An Indoor Localization Method Based on AOA and PDOA Using Virtual Stations in Multipath and NLOS Environments for Passive UHF RFID [J]. IEEE Access, 2018: 1-1.

[11] Shu Y, Huang Y, Zhang J, et al. Gradient-Based Fingerprinting for Indoor Localization and Tracking [J]. IEEE Transactions on Industrial Electronics, 2016, 63 (4): 2424-2433.

[12] Janicka J, Rapinski J. Application of RSSI Based Navigation in Indoor Positioning [J]. 2016: 45-50.

[13] Guan W G, Deng Z L, Ge Y T, et al. A Location Fingerprinting Algorithm Based on RSSI Statistic Parameters Matching Estimate [J]. Key Engineering Materials, 2011, 480-481: 1179-1184.

[14] Mundo L B D, Ansay R L D, Festin C A M, et al. A comparison of Wireless Fidelity (Wi-Fi) fingerprinting techniques [C]// International Conference on Ict Convergence. IEEE, 2011.

[15] Weixing X, Xianghong H, Qingquan L, et al. A New Weighted Algorithm Based on the Uneven Spatial Resolution of RSSI for Indoor Localization [J]. IEEE Access, 2018, 6: 26588-26595.