Research on WiFi Indoor Positioning Error Correction Method Based on Adaptive Genetic Algorithm

Fa-yue Zheng(✉)

Mechanical and Electronic Engineering School, Beijing Polytechnic, Beijing 100176, China
fayue766@sohu.com

Abstract. In view of the shortcomings of traditional mean filtering and Kalman filtering in the process of receiving indoor WiFi positioning signal, a new method of correction of indoor positioning error based on adaptive genetic algorithm is proposed. In order to improve the accuracy of dynamic adaptive genetic signal processing, the algorithm uses adaptive genetic algorithm to modify the singular value of the average distance per hop and the error of measurement distance, and then the modified adaptive genetic value is processed again by weighted filter. The simulation results show that the algorithm has high accuracy, and compared with mean filter and Kalman filter, the algorithm has a great improvement in the influence of average ranging error and communication radius on the error.

Keywords: Adaptive genetic algorithm · Wifi; Indoor positioning · Error correction

1 Introduction

In this paper, the WIFI indoor positioning method is deeply studied, the whole positioning method is simulated and verified by MATLAB, the key parameters of the positioning system are determined, and the field test is carried out. Based on the field test results, an indoor positioning method based on adaptive genetic algorithm is proposed, By removing some reference points with small reference value in the database and the unsuitable nearest points selected in the precise positioning, the positioning accuracy is improved to a certain extent [1]. Literature [2] proposed a WiFi calibration method using BP neural network: using outlier detection algorithm to eliminate outliers in different mobile phone RSSI data pairs, and obtain relatively pure data to input to the BP neural network for training; and The weights and bias values of each layer of the network are repeatedly updated, so that the output value is close to the true value; when the square sum of the output layer error is less than the threshold, the training is completed, and the weights and bias values of each layer can be saved to get a more stable network The calibration model can be used to calibrate the observations of different models of mobile phones. However, this method has a poor correction effect of wifi indoor positioning errors. Based

S. Liu and X. Ma (Eds.): ADHIP 2021, LNICST 416, pp. 377–388, 2022.
https://doi.org/10.1007/978-3-030-94551-0_30

on this, this paper proposes a wifi indoor positioning error correction method based on adaptive genetic algorithm. The multi-user group cooperative localization algorithm based on WiFi and acoustic ranging is further studied, and the ranging method based on the sum of the amplitude of multi frequency audible acoustic wave is proposed. After the ranging is completed, the adaptive genetic algorithm is used to process the WIFI single point positioning results and acoustic ranging results, which effectively improves the positioning accuracy. In order to further improve the positioning accuracy, this paper uses Kalman filter to track the trajectory of mobile terminal equipment. In order to solve the problem that the tracking error of standard Kalman filter is large when the mobile terminal equipment turns, a Kalman filter algorithm combined with indoor map is proposed. The information of indoor map and the speed direction estimation of mobile terminal equipment are used to judge the turn, and the parameters of Kalman filter are adjusted when the turn occurs, The tracking accuracy of the corner is greatly improved. The client of indoor positioning system is implemented on Android platform, and the positioning management server of positioning system is implemented on Windows/Linux platform. The performance of the proposed positioning and correction algorithm is verified by field test.

2 WiFi Indoor Positioning Error Correction Method

2.1 Wireless WiFi Indoor Positioning Technology

Wireless indoor positioning technology refers to the use of Bluetooth, RFID, infrared and WIFI technology to estimate the location of people or objects in the indoor environment. Similar to the outdoor environment, the indoor environment also has the problems of wireless signal multipath effect, shadow fading and interference. However, due to the complex internal structure of buildings, different building materials and various indoor items, the indoor wireless environment is more complex than the outdoor environment. The indoor positioning technology based on WIFI can directly use the existing WIFI access points in the building, with low deployment cost, which is a major advantage of WIFI Positioning [3]. The location method needs at least three known IP points. Assuming their coordinates are $\left(x_1, y_1\right)$, $\left(x_2,\ y_2\right)$ and $\left(x_3, y_3\right)$ respectively, the time of wireless signal passing through the mobile terminal and each IP point can be measured, so as to calculate the distance a1, a2, and a3 from each IP point to the mobile terminal equipment. Taking the position of the three IP points as the center of the circle and the distance between the corresponding IP point and the terminal equipment as the radius, the three circles can be determined, The coordinates of their unique intersection point are the positioning results of mobile terminal devices. The formula is as follows:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = a_1^2 \\ (x_2 - x)^2 + (y_2 - y)^2 = a_2^2 \\ (x_3 - x)^2 + (y_3 - y)^2 = a_3^2 \end{cases} \tag{1}$$

Where x and y represent the x and Y coordinates of the mobile terminal device respectively, where they are unknowns. By solving the above equations, the positioning results of mobile terminal devices can be obtained. TOA based location methods need to ensure strict time synchronization between IP and mobile terminal devices [4]. Adaptive genetic algorithm (AGA) is also based on signal transmission time, but AGA does not measure the absolute time of signal arrival, but the time difference between signals from mobile terminal devices and different IP. Therefore, the location method based on AGA does not need time synchronization between mobile terminal devices and each IP, However, strict time synchronization is needed between IPS [5]. The positioning principle is shown in the figure (Fig. 1).

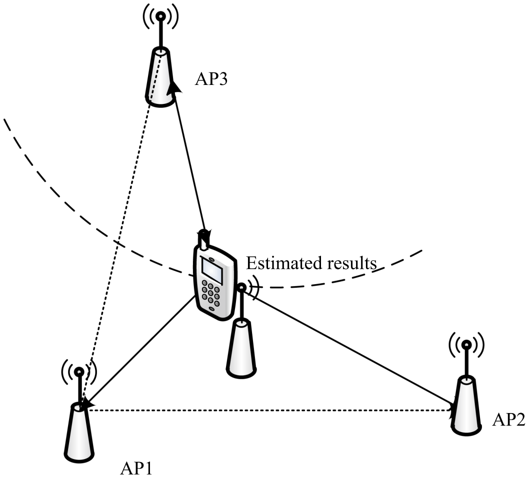

Fig. 1. Adaptive genetic algorithm indoor WiFi positioning principle

Adaptive genetic algorithm positioning requires at least three IP. During positioning, the time difference between the signal sent by the terminal equipment and each IP is measured:

$$\begin{cases} \sqrt{(a-x_2)^2-(b-y_2)^2}-\sqrt{(a-x_1)^2-(b-y_1)^2}=c(t_2-t_1) \\ \sqrt{(a-x_1)^2-(b-y_1)^2}-\sqrt{(a-x_3)^2-(b-y_3)^2}=c(t_1-t_3) \end{cases} \tag{2}$$

Among them, (a,b) represents the position coordinates of the mobile terminal to be located, and t_1, t_2 and t_3 respectively represent the time when the signal reaches the 3 IP. There may be two results calculated by the above formula, which will cause the positioning result to be blurred. At this time, the final positioning result can be determined by other information such as signal strength. When there are at least 4 IP, at least three hyperbolic equations can be obtained. At this time, the positioning result of the mobile terminal device can be uniquely determined [6]. If the position is known, the azimuth angle and length of the signal arriving at the IP are measured during positioning. Two straight lines can be obtained through the positions of the two IP and the azimuth angles of the two signals, and the intersection is the final positioning result. The position coordinate of the device to be located is (x, y), you can get:

$$\begin{cases} \tan\theta_1 = (y - y_1)/(x - x_1) \\ \tan\theta_2 = (y - y_2)/(x - x_2) \end{cases} \tag{3}$$

The positioning result can be obtained by solving the above-mentioned binary equations. The antenna array and other equipment are used to measure the angle of arrival of the signal, so the additional hardware equipment required is more complicated. The principle of indoor positioning using the wireless channel model is that the mobile terminal device estimates the distance between the terminal device and each IP by measuring the RSSI from multiple IP, and then uses the three-circle intersection positioning method to obtain the final positioning result. In the wireless channel model method, the most important thing is to have an accurate indoor wireless channel model. The accuracy of the channel model is directly related to the ranging accuracy using RSSI, thereby affecting the accuracy of the final positioning result [7]. When the transceiver device is in an open space and there are no obstacles between them, the received signal strength is inversely proportional to the square of the distance between the transceiver devices:

$$P_r \propto \frac{a_1^2 + a_2^2 + a_3^2 - 1}{d^2(\tan\theta_1 + \tan\theta_2)} \tag{4}$$

Through a lot of theoretical and experimental research, a specific formula is obtained:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L - P_r} \tag{5}$$

Where P_t represents the transmit power of the transmitting end, G_t and G_r represent the gain of the transmitting and receiving antennas respectively, λ represents the wavelength of the wireless signal, d represents the distance between the transmitting and receiving ends, and L represents the propagation loss [8]. Due to factors such as walls and other obstacles, people walking, door opening and closing, the indoor wireless environment is much more complicated than free space, so the free space attenuation model cannot be simply used for indoor positioning distance measurement. Through a large number of experiments, a logarithmic distance path attenuation model is summarized.

$$PL(d) = PL(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{6}$$

Among them, d_0 is the path attenuation index, the value of d_0 is different in different environments, and X represents the environmental noise, which obeys the normal distribution with the mean value of zero. d is the reference distance, usually 1 m. $PL(d_0)$ represents the loss at the reference distance; PL(d) represents the path loss value when the distance between the receiving and sending ends is d. The logarithmic path attenuation model does not include the penetration loss of the wireless signal from obstacles such as the floor and walls of the building, so the Keenan-Motley model is proposed:

$$PL(d) = L_0 + 10n\log_{10}(d) + \sum_{j=1}^{J} N_{wj} L_{wj} + \sum_{i=1}^{I} N_{fi} L_{fi} \tag{7}$$

Among them, L_{fi} represents the reference value of floor loss, and N_{fi} represents the number of penetrated floors. L_{wj} represents the reference value of through-wall loss. N_{wj} represents the number of through walls; other symbols have the same meaning as the logarithmic path attenuation model. As shown in the table, the penetration loss values of different building materials are different (Table 1).

Table 1. Penetration loss values of different building materials

Material type	Penetration loss (dB)
Ceiling management	1–8
Concrete floor	25–30
Ordinary brick concrete partition wall	10–15
Concrete wall	20–30
Elevator box top	30
Wooden furniture	3–6
Glass	5–8

During positioning, selecting an accurate indoor wireless attenuation model can obtain more accurate ranging results, thereby reducing the final positioning error.

2.2 Wifi Indoor Positioning Error

The quality of indoor positioning technology cannot be evaluated from a single aspect, but needs to be evaluated from various aspects such as positioning accuracy, deployment cost, and energy consumption. Indoor map is an important part and implementation basis of indoor positioning system. Without indoor map, the collection of location database and the display of final positioning results cannot be completed. The Arc GIS system is used to draw and publish the map. This geographic information system is developed by Esri [9]. The model structure of the Arc GIS system includes object classes, feature classes, and feature datasets. The Arc GIS indoor map of the realized indoor positioning system is deployed in the positioning and map server. First, the experimental area is measured geographically, and then the indoor map is drawn in the Arc GIS Desktop software based on the measurement information to generate the indoor map database, and finally in Arc GIS Publish the drawn indoor map in the Server and start the Arc GIS service to complete the drawing and deployment of the Arc GIS indoor map. The Android client can obtain the indoor map of the relevant area from the map server in real time, or convert the Arc GIS indoor map to an offline map and store it in the client. The client can display the indoor map on the screen, and zoom or zoom the map. Rotate, the final indoor positioning result can also be displayed on the map intuitively in real time. It should be noted here that if the client needs to obtain the Arc GIS indoor map from the map server in real time, the map server needs to close the firewall or set certain firewall rules, otherwise the client may not be able to obtain map data from the map server (Fig. 2).

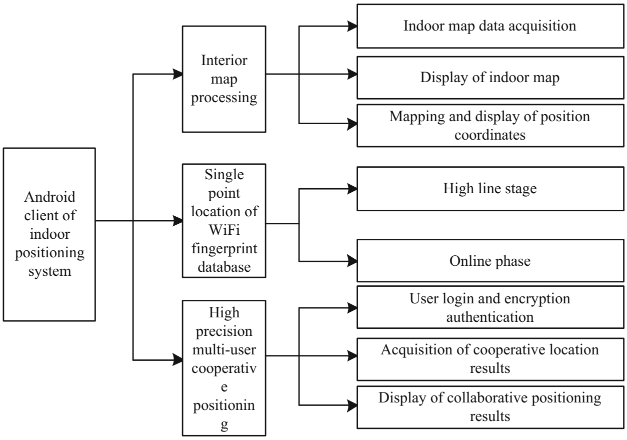

Fig. 2. Wifi indoor positioning data processing model

Positioning accuracy is the most important indicator, which depends on the positioning method and positioning algorithm. Generally, high precision means high deployment cost and high computational complexity. The positioning accuracy can be evaluated from the average positioning error, the cumulative distribution function of the positioning error, and the mean square positioning error. In a two-dimensional plane, if n single-point positioning experiments are performed, and the actual coordinates of the n points to be positioned are $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, then the average positioning error of the n times of positioning is:

$$ME = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left(x_i - \hat{x}_i\right)^2 + \left(y_i - \hat{y}_i\right)^2} \tag{8}$$

The mean square positioning error is

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[\left(x_i - \hat{x}_i\right)^2 + \left(y_i - \hat{y}_i\right)^2\right] \tag{9}$$

Further, the root mean square positioning error is:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\left(x_i - \hat{x}_i\right)^2 + \left(y_i - \hat{y}_i\right)^2\right]} \tag{10}$$

The CDF of the positioning error represents the probability of the positioning error within a certain range, and the CDF curve can more intuitively describe the error performance of the positioning system. The main work done in the offline phase is the construction of the WIFI location. When the positioning area is large, the number of reference points is large, and the amount of data may be very large. Therefore, when the positioning point is compared with the received signal strength of each reference point during online positioning, the calculation complexity is high, and the effect of real-time positioning cannot be achieved.. In order to solve this problem, a clustering algorithm is used to classify the reference points to form a certain number of clusters, which can greatly reduce the amount of calculation during positioning and improve the real-time performance of indoor positioning [10]. During the measurement process, the dynamic adaptive genetic algorithm often encounters some sudden singular values due to factors such as equipment or environment, and these singular values often bring great errors to the positioning. In the mean value and Kalman filtering methods, these singular values cannot be eliminated or corrected in real time, so errors caused by singular values cannot be eliminated. Accordingly, this paper proposes an improved dynamic adaptive genetic algorithm ranging model, as shown in the figure (Fig. 3):

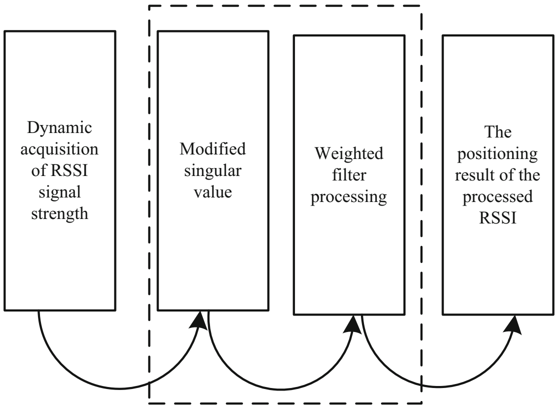

Fig. 3. Improved dynamic positioning algorithm

Specifically, it is divided into three parts: the first part is the dynamic acquisition of adaptive genetic signals; the second part is adaptive genetic signal processing, and this part is divided into two processes: singular value correction and weighted filtering; the third part is after processing Adaptive genetic and result output.

2.3 Wifi Indoor Positioning Error Correction

The online positioning phase completes the actual positioning process of the mobile terminal device, which is specifically divided into two processes, namely, rough positioning and precise positioning. The purpose of rough positioning is to narrow the to-be-positioned point from the entire positioning area to one or several clusters through cluster matching. Through rough positioning, the current position of the point to be located can be roughly determined, so there are fewer reference points to consider, which greatly reduces the number of reference points that need to be compared during the precise positioning stage and improves the positioning speed. When positioning, the mobile device first scans the RSSI of all access points it can currently detect:

$$\Phi_r = [\varphi_1, \varphi_2, \ldots, \varphi_L] \tag{11}$$

Among them, φ_i represents the RSSI from the i access point collected by the mobile terminal equipment in any direction, and L represents the total number of access points in the database. The co-location algorithm based on error diversity makes full use of the diversity of single-point positioning errors, and merges the received single-point position estimation results of surrounding users and itself to improve its own positioning accuracy. First, the user obtains his own single-point positioning result through the PDR positioning method, and then exchanges this result with the surrounding users, and processes the single-point positioning result of himself and the surrounding co-locators to obtain a coordinated positioning result with improved positioning accuracy.

This co-location method has designed a sound wave communication method, which can effectively exchange position estimation information of users by distinguishing the frequency of sound waves when they meet. In addition, experimental studies have proved that when users use PDR for positioning, the estimation error of the movement step size and the estimation error of the movement direction obey the normal distribution. Therefore, if the PDR positioning results of multiple users at the same or similar positions are averaged, different users can be averaged. The single-point positioning errors cancel each other out, resulting in higher positioning accuracy at this position. The block diagram of co-location based on error diversity is shown in the figure, and the specific implementation steps are as follows (Fig. 4):

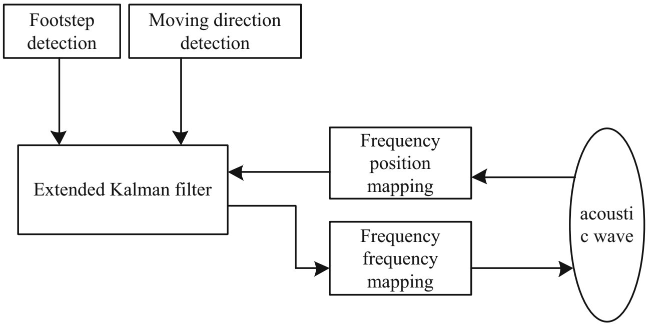

Fig. 4. Block diagram of co-location based on error diversity

As shown in the figure, the location area of interest is divided into different virtual grid areas. Each grid has a number as the grid label, which represents this grid area. As long as the grid size is determined, the entire grid can be covered by the grid. Indoor map. The disadvantage of the co-location algorithm based on error diversity is that due to the limited sound wave frequency range, each grid area corresponds to a sound wave frequency, so the total number of grid areas is limited, and the grid area is not fine enough, and users use sound waves. When the frequency exchanges position information, the center point of the regional grid is used as its own positioning coordinate, which brings about larger errors. In addition, this method only uses the diversity of single-point positioning errors for collaborative positioning, and does not make full use of the geometric relationship between the positioning results of multiple users, so that the improvement of positioning accuracy is relatively limited.

3 Analysis of Results

In order to study the ranging performance of the dual-transmit and dual-receive Chirp sonic ranging method used in this article, this article uses four mobile phones to conduct a ranging experiment indoors (Table 2).

Table 2. Basic configuration parameter list of four mobile phones

Basic configuration	HTC T328	Samsung S7568	Samsung I 9100	HTC G7
operating system	Android OS 4.0	Android OS 4.0	Android OS 2.3	Android OS2.2
CPU	Snapdragon MSM7227A	Snapdragon MSM7227A	Samsuing Exynos 4210	Snapdragon QSD8250
Wi Fi module	Broadcom BCM4329	Unknown	Samsung SWB-B23	Broadcom BCM4329

The statistical parameters of the RSSI sample data collected by different mobile terminals are compared, including the maximum and minimum values, the range of change, and so on. The maximum value is measured by measuring the mobile phone as close to a certain IP as possible. Similarly, the minimum value is measured by measuring the maximum distance from a certain IP but still being able to collect its RSSI data. As shown in the table (Table 3).

Table 3. Comparison of the maximum, minimum and variation range of RSSI data collected by different mobile terminals

Manufacturer	Mobile phone model	Minimum (dBm)	Maximum (dBm)	Range of change (dBm)
HTC	G7	−96	−38	61
HTC	T328	−97	−35	59
Samsung	GTS7568	−93	−13	80
Samsung	I9100	−95	−24	71

Samsung GTS7_568 has the largest variation range, which means that it converts the real signal energy in more detail and can recognize a larger range of signal changes. In contrast, the RSSI sample data collected by HTCG7 has the smallest change range. Therefore, this may cause the true signal energy within a certain range to be mapped to the same RSSI value, which makes the RSSI change range it can detect even smaller. For alignment, a larger RSSI variation means a higher degree of discrimination of signal energy, which is more helpful to distinguish two different positions and improve positioning accuracy. In the experiment, 200 different distance tests were selected, and the distance measurement error was counted. The figure shows the CDF curve of the ranging error (Fig. 5).

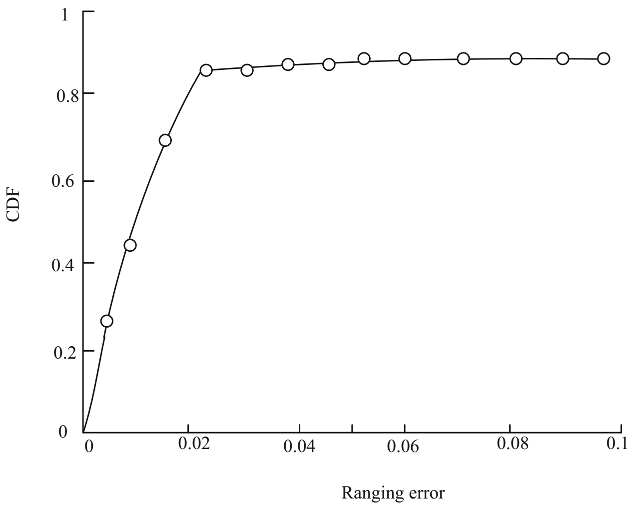

Fig. 5. CDF curve of signal ranging error

Obviously, the probability of ranging error within 3 cm is more than 90%, the probability of error within 8 cm is 100%, and the average error is 1.13 cm, which has reached an ideal ranging accuracy. Through experiments, the range of the dual-transmit and dual-receive Chirp sonic ranging can reach 8 m. In order to verify the feasibility of this algorithm, simulation comparisons are performed based on the mean filtering method, Kalman filtering method and improved dynamic adaptive genetic algorithm. The comparison results of average positioning error and node communication radius error are shown in the figure. The experimental parameters are set as follows (Figs. 6 and 7):

① The network area is set to a two-dimensional plane of 80 m*80 m;

② Randomly deploy 20 unknown nodes in this area;

③ In order to verify the influence of the distribution density of anchor nodes in the network on the positioning error of the algorithm, the number of anchor nodes in this area is 20–50 respectively. In order to simulate the actual situation, the anchor nodes are randomly distributed;

④ Communication radius: $r = 50$ m;

⑤ All experiments are simulated for 50 times, and the average value is taken as the experimental result;

⑥ Reference distance $d0 = 1$, mean square error of Gaussian distribution $X\sigma = 2$.

It can be seen from the figure that with the increase of the number of anchor nodes in the network, the average positioning error of the mean filtering method, Kalman filtering method and improved dynamic adaptive genetic algorithm proposed in this paper is generally decreasing. As the number of anchor nodes increases, the average positioning errors of the three algorithms tend to stabilize. When the number of anchor

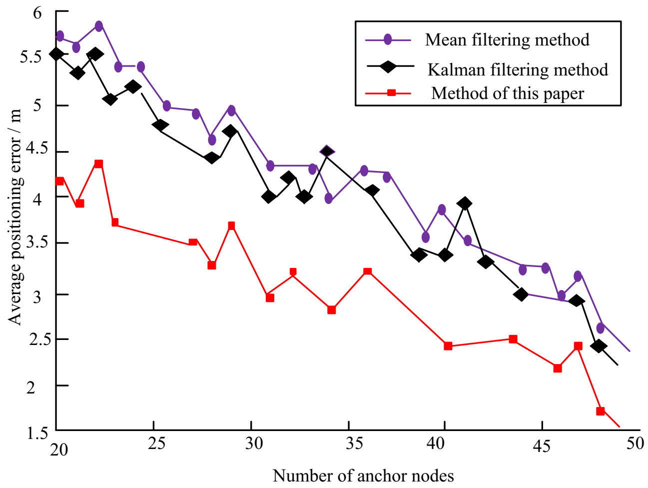

Fig. 6. Comparison of average errors of different algorithms

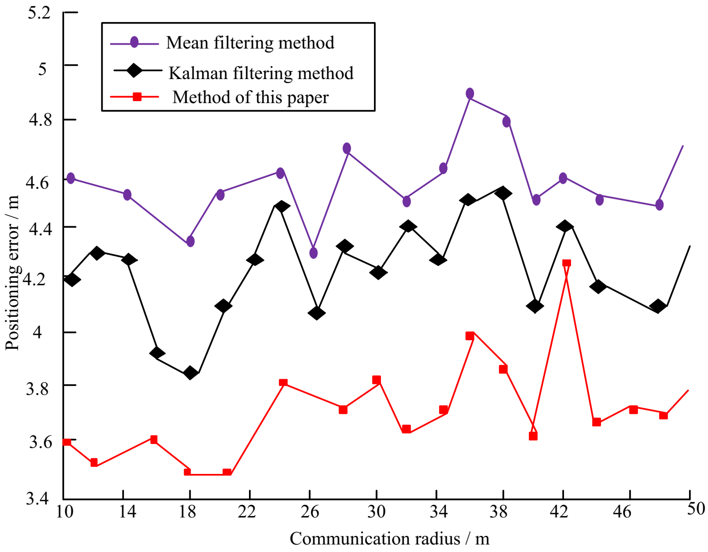

Fig. 7. The influence of node communication radius on error

nodes is 34, 41, and 46, the average positioning error of Kalman filtering is greater than that of average filtering. As the density of anchor nodes in the network increases, the average positioning error of the two methods tends to be equal; the average positioning error of the improved dynamic adaptive genetic algorithm is significantly smaller than that of the first two algorithms, indicating that the improved method can better suppress a single time The influence of the measured value on the average positioning error of the algorithm.

4 Conclusion

Aiming at the shortcomings of the existing mean filter method and Kalman filter method that the singular values cannot be eliminated and corrected in real time, a wifi indoor positioning error correction method based on adaptive genetic algorithm is introduced, and the weighted filter method is used to process the corrected self Adapt to genetic value. For multiple sets of adaptive genetic values measured by anchor nodes, a median strategy is adopted to select the most appropriate adaptive genetic values. Aiming at the problem that the target node and the anchor node are at different heights, a space compensation model is designed to reduce the impact of the target node and the anchor node on the positioning accuracy caused by the different planes. The simulation experiment results show that the algorithm improves the accuracy of dynamic adaptive genetic signal processing, has a higher calculation accuracy, and the ranging error after filtering has been greatly improved. Each parameter in the adopted environmental attenuation factor needs to be re-calibrated under the new environment, so the workload is relatively large. In future work, we can test several more model parameters in indoor environments, and then summarize a set of model parameters that can be used directly in indoor environments.

Fund Projects. Research on WiFi Based indoor positioning technology (Project No.: CJGX2016-KY-YZK040).

References

1. So, C., Ho, I.M., Chae, J.S., et al.: PWR core loading pattern optimization with adaptive genetic algorithm. Ann. Nucl. Energy **159**(9), 108331 (2021)
2. Song Binbin, Y., Min, H.X., et al.: A WiFi calibration method for indoor positioning based on BP neural network. J. Navig. Positioning **7**(01), 43–47 (2019)
3. Dbna, B., Jing, H.A., Vtt, A., et al.: An effective random statistical method for indoor positioning system using WiFi fingerprinting - ScienceDirect. Futur. Gener. Comput. Syst. **109**(8), 238–248 (2020)
4. Han K , Yu S M , Kim S L , et al. Exploiting User Mobility for WiFi RTT Positioning: A Geometric Approach[J]. IEEE Internet of Things Journal, 2021, PP(99):1–1
5. Al-Khaleefa, A., Ahmad, M.R., Isa, A., et al.: MFA-OSELM Algorithm for WiFi-based indoor positioning system. Inf. (Switzerland) **10**(4), 146 (2019)
6. Martin-Escalona, I., Zola, E.: Passive round-trip-time positioning in dense IEEE 802.11 Networks. Electronics **9**(8), 1193 (2020)
7. Madyatmadja, E.D., Hakim, L., Tannady, H., et al.: Use K-Nearest NEIGHBOR and FLOYD WARSHALL algorithms to determine store location and distance based on WIFI. Tech. Rep. Kansai Univ. **62**(5), 2379–2389 (2020)
8. Liu, S., Sun, G., Fu, W. (eds.): 2020. LNICSSITE, vol. 339. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-63952-5
9. Liu, S., Liu, X., Wang, S., Muhammad, K.: Fuzzy-Aided Solution for Out-of-View Challenge in Visual Tracking under IoT Assisted Complex Environment. Neural Comput. Appl. **33**(4), 1055–1065 (2021)
10. Liu, S., Li, Z., Zhang, Y., Cheng, X.: Introduction of key problems in long-distance learning and training. Mob. Netw. Appl. **24**(1), 1–4 (2018). https://doi.org/10.1007/s11036-018-1136-6