The Application of Wireless Sensor Network in Public Environment Art Design

Tengjiao Liu

School of Art and Design, Xi'an Fanyi University, Xi'an, Shaanxi, 710105, China
liutengjiao@xafy.edu.cn

Abstract: *In recent years, affected by the hot development of information technology, big data technology has been fully expanded, and wireless sensor networks, which are popular with their own characteristics, have also ushered in vigorous development. Based on the current emphasis on the public environment, the use of wireless sensor networks to locate the details of the environment has the most fundamental and important impact on the artistic design of the environment. Designs that conform to the concept of environmental development are more in line with public expectations. Based on this, this article proposes a wireless sensor network-based public environment for buildings. Environmental positioning research explores the development of intelligent building environment. This article mainly discusses the application technology of wireless sensor positioning system, and compares the modified positioning algorithm with other positioning algorithms. Under the same acquisition conditions and under the same number of samples, explore the difference in positioning errors. A hybrid positioning system based on multiple positioning algorithms is proposed, and comparative experiments are carried out to obtain experimental results, which can highlight the effectiveness of the results. The experimental results in this paper show that the area judgment of the TOA internal area is very good, with an accuracy rate of 100%; the accuracy rate of the key areas of the corridor is 89%. When the wrong area discrimination occurs in the key area of the corridor, it will cause the time delay of the positioning mode switch. The main influence factor is the interference of the door and wall to the key area range, indicating that more attention should be paid to it in the measurement.*

Keywords: *Wireless Sensors, Public Environment, Intelligent Building Monitoring, Artistic Design Positioning*

1. Introduction

With the rapid development of society, people have begun to enter the era of big data information. Wireless sensor networks, which are inseparable from the Internet, are used in many fields with their own perceptual advantages. Many scholars at home and abroad have developed them. Among them, CMIMO strategy is the main candidate to realize green communication in wireless sensor network. Improve the performance of CMIMO by using emerging technologies such as spatial modulation and coding. Although some breakthroughs have been made in this area, the problem of how to accurately model CMIMO using these emerging technologies is far from being fully understood. Peng Y investigated several state-of-the-art CMIMO models for different scenarios, including data aggregation, multi-hop based and clustering schemes. In addition, it also discussed the implementation of CMIMO technology, which is expected to become a candidate technology for green communication in modern applications [1]. With the development of cloud computing, sensor networks can be combined with the cloud to expand its computing and storage capabilities. Wang T reviewed the current sensor cloud literature and found that the existing sensor cloud still has some problems, such as high time lag, weak reliability, and security risks. According to their investigation, fog computing, as a new computing architecture, can solve the above problems by introducing elastic resources and local services to the underlying sensors. We also specifically studied the characteristics of fog computing in WSN, and then proposed a new fog computing framework in which multiple mobile elements are used to bridge WSN and cloud [2]. Choosing the appropriate encryption primitives and integrating them into the security protocol determines the largest part of the efficiency and energy consumption of the wireless sensor network (WSN). There are many investigations on WSN security issues, however, these investigations did not focus on the public key cryptographic primitives in WSN. Shim K A has an in-depth understanding of the public key cryptographic primitives in WSN, including identity-based

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

cryptography, and discussed their main directions and some open research issues that can be further developed [3]. Luo J's research focuses on minimizing energy consumption and maximizing the network life of data relay in one-dimensional (1-D) queue networks. A large number of simulation and real test results show that compared with other existing WSN routing schemes, the proposed solution ENS_OR can significantly improve the performance of the network in terms of energy saving and wireless connection [4]. Service-Oriented Architecture (SOA) is a software architecture that can be integrated with WSN applications to meet these challenges. SOA middleware bridges the gap between the advanced requirements of different applications and the hardware limitations of WSN. The Remah A survey explored state-of-the-art methods based on SOA and service-oriented middleware (SOM) architectures that provide solutions to WSN challenges. In addition, the characteristics of WSN's SOA and middleware architecture are compared to achieve more robust and efficient network performance. Summarized the future research direction of SOM architecture to meet all the requirements of WSN emerging applications [5]. Kunz T briefly introduced the main methods of software-based node location in WSN. A type of positioning protocol with good positioning performance puts together a local map of relative coordinates into a global coordinate map. These protocols require some nodes whose absolute coordinates are known, called anchor nodes. Although there are many factors that affect the position error of nodes, in this type of protocol, using Procrustes analysis, the placement of anchor nodes will significantly affect the error. It also shows the impact of anchor node placement and proposes a set of guidelines to ensure the best results, while using the least number of anchor nodes possible [6]. Designing effective and efficient event detection technology to deal with the limited resources of WSN is the goal of this research. Event detection can be done in two ways: (1) centralized (in the base station) and (2) decentralized (in the network). In this research, Havinga P focuses on decentralized event detection, where sensor nodes use artificial intelligence, data fusion, and distributed pattern recognition to execute locally in the WSN to collaboratively detect events. Since WSN can be deployed in different environments (contexts) for different applications, the number and types of events may be different in different environments and contexts [7]. Many of the above scholars have their own uniqueness in the application research of wireless sensor networks, but there are often various errors in the experiment process, which makes the calculation process complicated and the accuracy of the experimental results has a certain degree of difference sex.

The most important manifestation of the innovation of this article is that the detection of building environment in the public environment uses wireless sensors as the main research mode combined with big data analysis, and it is based on the fact that most scholars only carried out a detailed description of one method. Elaboration, and lack of comparative data, it is impossible to clearly see the excellent points of the improvement. On the basis of its own, this article lists a variety of algorithms with the same effect for comparison, and also proposes a hybrid positioning detection system.

2. Wireless Sensor Network

2.1 The Development Background of Wireless Sensor Networks

Wireless sensor networks have been widely used in various fields with their own advantages and characteristics. Over time, wireless sensors are welcomed by researchers with their low cost and low power consumption characteristics [8]. The size of the sensor is becoming more and more miniaturized with the development of social scientific and technological information [9]. As shown in Figure 1.

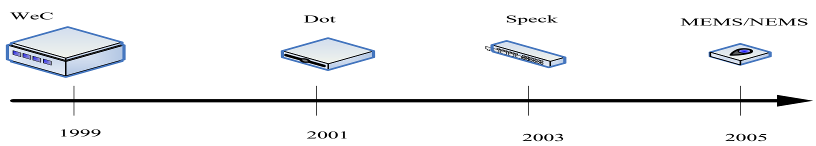


Figure 1: Sensor nodes

Wireless sensor network technology overcomes the limitation of the scope of a single sensor node, and effectively expands the spatial range of information perception [10-11].

2.2 Wireless Sensor Network Architecture Design

Figure 2 shows the architecture of the building environment monitoring system. The entire system consists of a wireless sensor network deployed in the building for environmental parameter data collection, and a monitoring software platform running on a data server for data storage and analysis

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

[12-13].

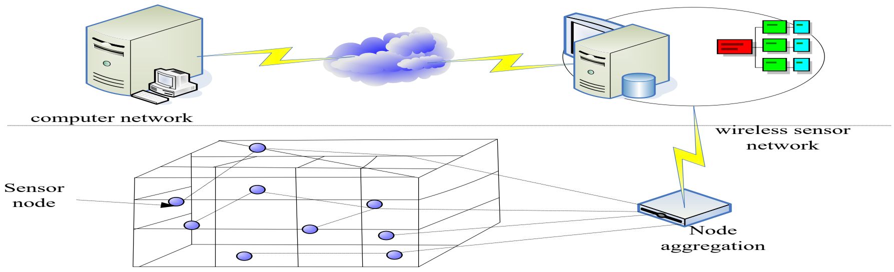


Figure 2: Intelligent monitoring structure of public buildings based on wireless sensors

Wireless sensor networks are used for the collection, transmission and convergence of environmental data in smart buildings [14]. The sensor network has a tree network topology structure composed of sensor nodes, cluster head nodes and aggregation nodes to realize the transformation of sensor data flow from generation to aggregation [15-16].

2.3 Sensor Model

Consider a wireless sensor network with X wireless sensors and a monitoring target, and assume that there is noise between the target and the sensor. The noise is independent and identically distributed, following the standard Gaussian distribution, with a mean value of zero and a variance in units. As shown in Figure 3, X distributed sensors are uniformly deployed in the ROI, the whole is in the shape of a quadratic function, and the range of the target appearance is 2b, which is random. The location of the local sensor is unknown to the HE. Each local sensor first monitors the ROI, makes a local judgment on whether the target appears, and then sends the judgment to the HE to make a global judgment on whether the target appears.

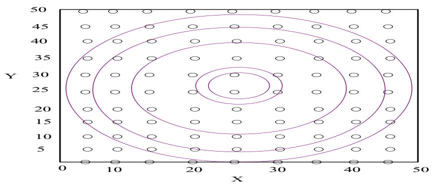


Figure 3: Layout of local sensors

From Figure 3, we can see that the local wireless sensor a is assumed to be binary, which is expressed as follows:

$$\mathrm{Fa}:\ c_a = \mathrm{Ba} + \mathrm{Xa}$$
$$F_0:\ c_a = \mathrm{Xa} \tag{1}$$

The presence and absence of the hypothetical target in the equation are represented by Fa and F_0 respectively, which comply with the standardized Gaussian distribution, and use Xa to represent noise, as follows:

$$\mathrm{Xa} \sim X(0,1) \tag{2}$$

In the above equation (1), the signals received and detected in area a are denoted as c_a and Ba, respectively. The transmitted signal power will attenuate as the distance increases, and the power attenuation model can be expressed as:

$$\mathrm{Ba} = y(La) \tag{3}$$

The La representing the distance between the target and the local wireless sensor in the equation is expressed as:

$$\mathrm{La} = \sqrt{(\mathrm{Aa}-\mathrm{At})^2 + (\mathrm{Ba}-\mathrm{Bt})^2} \tag{4}$$

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

The coordinates of point a of the local wireless sensor in equation (4) are expressed as (Aa, Ba). The target coordinates are expressed as (At, Bt). In equation (3), y(.) represents the attenuation function, and there are many expressions. The expression in this article is:

$$y(a)=\begin{cases} q0 \\ a^{b}A\geq b_0 \end{cases} \tag{5}$$

Among them, the power of the signal transmitted by the target at a certain distance b_0 is $q0$, and α represents the index of attenuation. The attenuation function used in this article is expressed as follows:

$$Y(La)=\sqrt{\frac{q0}{1+\lambda b_a^{\alpha}}} \tag{6}$$

In the distributed detection of wireless sensor networks, the local observations must be quantified before being sent to the HE, which is required to make the final decision about the existence of the target.

3. Comparative Experiment of Multiple Positioning Based on Wireless Sensors

3.1 Toa Indoor Positioning Technology Based on Wireless Sensors

(1) TOA's ranging principle

TOA distance measurement requires precise time synchronization between two nodes, which places strict requirements on the hardware. SDS-TWR is a technology to improve TOA distance measurement. It can theoretically suppress errors caused by clock drift, because it basically does not require time synchronization between distance nodes. The process of distance measurement using SDS-TWR is shown in Figure 4.

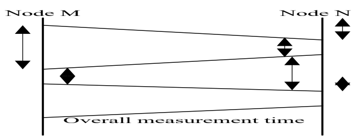


Figure 4: Schematic diagram of the ranging process

It can be seen from Figure 4 that once a single ranging starts, the signal is sent from node M to node N. After M sends the signal, the measurement starts, and the node N acknowledges the signal, which means that the ranging request has been received. Then, when node M receives the confirmation frame from node N, the measurement is over, that is, the first side of the bilateral measurement is completed. Then start and complete the second side measurement from node N to node M. Assuming that the signal propagation in the air has a time delay F_{pr}, from Figure 4 we can draw equation (7) as follows

$$\begin{aligned} F_{roundM} &= 2F_{pr}+F_{repN} \\ F_{roundN} &= 2F_{pr}+F_{repM} \end{aligned} \tag{7}$$

Simplify equation (7), and find the signal propagation delay F_{pr} as:

$$F_{pr}=\frac{1}{4}\cdot(F_{roundM}-F_{repN}+F_{roundN}-F_{repM}) \tag{8}$$

Use delay propagation to multiply the propagation speed U of the wireless signal in the medium to obtain the node distance L:

$$L=U\cdot F_{pr}=\frac{1}{4}(F_{roundM}-F_{repN}+F_{roundN}-F_{repM})\cdot U \tag{9}$$

In the actual detection process, the crystal oscillator drifts due to the limitation of the conditions.

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

Assuming that the drifts of the M and N points are V_M and V_N, the offset error generated in this section is:

$$\Delta F = \frac{(F_{repN} - F_{repM})(V_M - V_N)}{4} \tag{10}$$

It can be seen from Equation 10 that the ranging method can effectively suppress the error generated by the crystal oscillator offset.

(2) NLOS error suppression based on improved Kalman filter

The state equation and measurement equation are shown in Equation 11.

$$B(R+1) = XB(R) + M(R) \tag{11}$$

$$S(R) = YB(R) + U(R) \tag{12}$$

In the above equations, $B(R)$ and $S(R)$ represent the matrix of the transition and measurement of state and measurement vectors X and Y, and $M(R)$ and $U(R)$ represent the noise vector during the process and during the measurement, respectively.

The recursive process of Kalman filtering is as follows:

$$\hat{B}_R = X\hat{B}_{R-1} \tag{13}$$

$$\hat{q}R = X\hat{q}_{R-1}X^t + P \tag{14}$$

$$C_R = S_R - Y\hat{B}_R \tag{15}$$

$$F_R = \hat{q}_R Y^t (Y_R \hat{q}_R Y_R^t + K)^{-1} \tag{16}$$

$$\hat{B}_R = \hat{B}_R + R_R C_R \tag{17}$$

$$\hat{q}_R = (1 - R_R Y_R)\hat{q}_R \tag{18}$$

In the above recursive equation, P and K respectively represent the covariance matrix of the noise vector during the process and during the measurement, while $\hat{B}_R$ represents the predicted estimated value of the state vector, and $\hat{q}_R$ represents the covariance of the current estimated and estimated errors. The variance matrix, C_R and R_R are the measured information and Kalman value added.

Improve the error suppression effect of the Kalman filter algorithm: Figure 5 shows that there is an unknown node N and multiple nodes with known coordinates. We assume that it moves from R-1 to the position at R, and detects the unknown node by detecting the R time. , Get the representation of its distance $La(R)$, $Lb(R)$, $Lx(R)$.

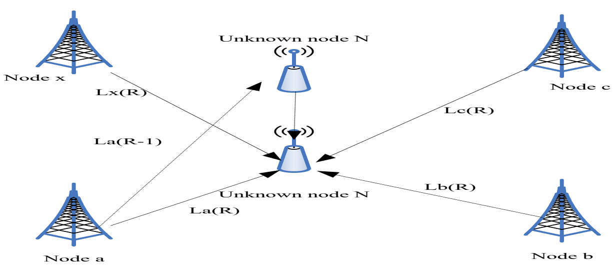


Figure 5: Node positioning in wireless sensor network

It can be seen from Figure 5 that R-1 and R and node a are in a triangular structure, and the measured angle α is based on the law of cosines:

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

$$-1 \le \cos\alpha \le 1 \tag{19}$$

$$\mathrm{BR}^2 = \mathrm{L}a(R)^2 + \mathrm{L}a(R-1)^2 - 2\cdot \mathrm{L}a(R)\cdot \mathrm{L}a(R-1)\cdot\cos\alpha \tag{20}$$

Hypothesis

$$\mathrm{L}a(R-1) = da(R), B\mathrm{R} = Lb\cdot La(R) \tag{21}$$

Incorporating equations (19) and (20), La≈1 can be obtained. From this, it can be concluded that for indoor positioning, an unknown moving target can be regarded as a uniform and low-speed state of motion, and equations can be established through them.

In order to solve the shortcomings of traditional Kalman filter in NLOS error suppression, it is necessary to improve the Kalman filter algorithm to achieve high-precision indoor positioning in both NLOS and LOS environments. For NLOS error suppression, the improved Kalman filter algorithm written by Matlab is used to process the same amount of data collected in the ranging experiment, and the traditional Kalman and the biased Kalman algorithm are used for comparison.

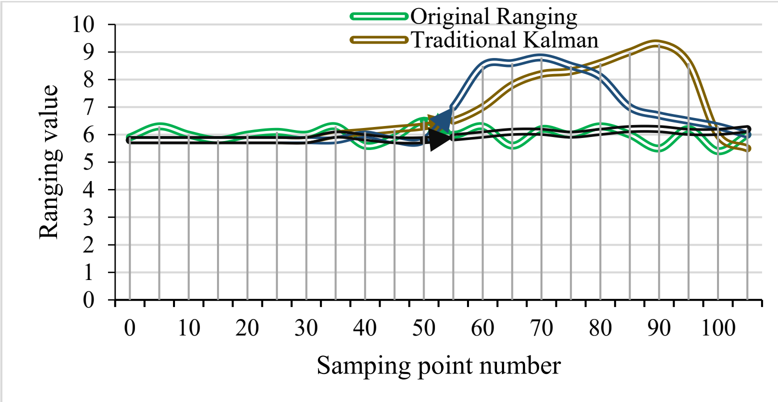
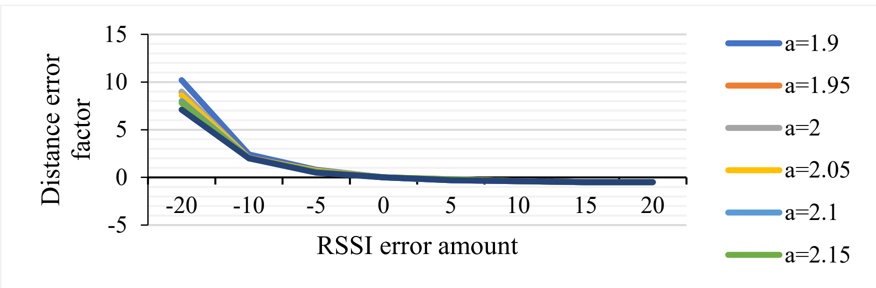


Figure 6: The effect of different filtering algorithms on error suppression

As shown in Figure 6, the traditional Kalman filter algorithm tracks the NLOS error so that the filtered distance value is much greater than the true value. When the NLOS interference disappears, the correction process will continue for a period of time due to the recursive effect of the filter, resulting in excessive correction. The biased Kalman filter algorithm has a certain inhibitory effect on NLOS interference due to the introduction of the estimation of the NLOS error, but because it does not introduce the estimation of the NLOS error to the biased Kalman filter algorithm, it has a certain inhibitory effect on the NLOS interference. However, since there is no correction to the filtering state parameters, there are still insufficient corrections and over corrections. From the perspective of correcting the error state information in the NLOS state, this paper uses the recursive characteristics of the filter to use the state estimation value in the LOS environment to modify the parameter amount in the NLOS environment in the nearest time to achieve the purpose of suppressing the NLOS interference.

3.2 Location Fingerprint Positioning Technology Based on Wifi

(1) RSSI propagation model and signal characteristic analysis



ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

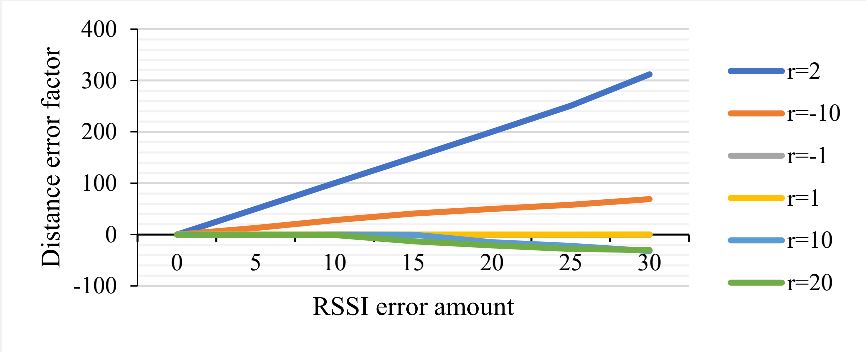


Figure 7: The relationship between distance errors factors in different environments

It can be seen from Figures 7(1) and 7(2) that different path loss factors will affect the error coefficient. Among them, the RSSI measurement error has a very large impact on the error coefficient, and the amplitude is negative. The distance error is equal to the product of the error coefficient and the actual distance, that is, if the error coefficient remains unchanged, the greater the actual distance, the greater the distance error. When using RSSI distance measurement to locate a large area, because of the principle, the distance measurement will cause a large distance error, so in practice, the fingerprint location method should be used instead.

(2) Analysis of the volatility of non-line-of-sight errors

Due to the complexity of the actual indoor environment and the randomness of the above-mentioned factors, the volatility of RSSI signals is often not recursive to the influence of certain specific factors. In this paper, the positioning experiment is done in the outdoor corridor environment of the building. The experiment is shown in Figure 8:

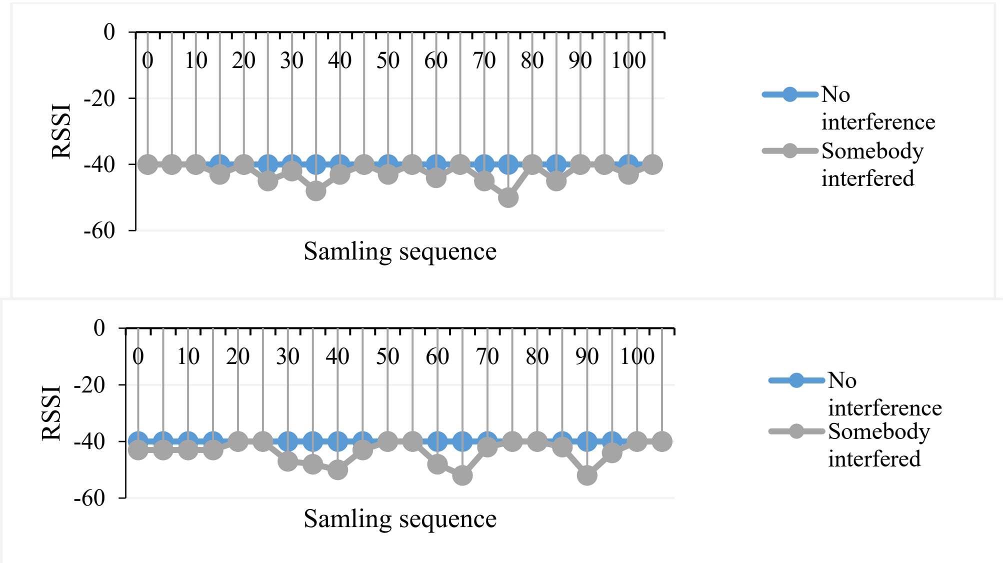


Figure 8: RSSI sampling with or without human interference

As shown in Figure 8, in the corridor environment of the building, the signal strength of the same WIFI router is measured multiple times when there is no interference around the node at a fixed position. It can be seen from the sampling curve that when there is no interference in the environment, the measured value fluctuates around a certain value and has a certain amplitude. In the presence of random non-visual interference in the environment, the measured value of RSSI will fluctuate with a large amplitude, and some measured values are far from the true value.

(3) Principle of fingerprint positioning based on WIFI: Kalman's RSSI filter

In the experiment, the WIFI anchor node and the laptop are placed at a distance of 4 meters from each other. In an unmanned environment, the RSSI value of WIFI is collected and processed by Kalman filtering algorithm. In order to compare with other filtering algorithms, the experimental data are also processed with moving average filtering, median filtering and Gaussian filtering.

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

In the same place, when people in the environment often walk between nodes, and there is a strong random non-line-of-sight connection, the RSSI measurement value and its filtering results are shown in Table 1.

Table 1: Four kinds of filtering data

Filtering algorithm	RSSI mean	Standard deviation of error	Mean error
Moving average filter	-41	3.2	-2.9
Median filter	-40.4	2.2	-2.3
Gaussian filtering	-40.8	3.2	-2.6
Kalman filter	-40.7	0.9	-2.6

Combining the analysis of Table 1, it can be seen that the non-visual interference in the environment is inherently random, which will cause changes in the electromagnetic wave propagation characteristics and cause the RSSI value to fluctuate drastically. The above four filters will have a certain degree of deviation from the actual value in a quiet environment, which is related to the change of the RSSI propagation characteristics. The mean square error analysis shows that the smoothing effect of the Kalman filter is better than the other three filters. In view of the moving average filter can well suppress the periodic interference, the mean square filter can well suppress the impulsive interference, the Gaussian filter can handle the low probability of large interference events, and the interference in the non-visual field has no periodic characteristics when it occurs. And their duration may be short or continuous. The Kalman filter used in this work uses the best estimation standard to recover the signal. This standard has a strong ability to recover from continuous interference signals, and it can output RSSI. The result is the best smoothing effect.

(4) RSSI fingerprint map establishment

The working process of WIFI positioning technology is mainly divided into two stages: offline RSSI database establishment and online position calculation. The main principle is shown in Figure 9:

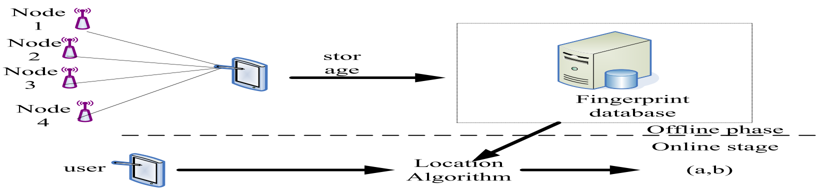


Figure 9: Principle of fingerprint positioning based on wifi

In the offline collection phase of WIFI fingerprint positioning, by recording the RSSI value of the preset position coordinates of the sampling point and the positioning anchor node, the index relationship between the position and the RSSI signal feature is established, and the database is established according to the prescribed format. Under normal circumstances, a large number of sampling reference points need to be selected to ensure that the fingerprint database can fully and detailedly reflect the RSSI performance of different physical locations in the positioning area, which undoubtedly increases the cost of fingerprint positioning. At the same time, as time goes by, the initially created RSSI fingerprint information will become invalid with changes in the location area environment (for example, due to changes in anchor node positions, changes in household layout, and other factors), so the fingerprint database needs to be updated regularly. Therefore, how to manage and update the RSSI fingerprint database meaningfully and effectively is an important issue on the road to practical application of fingerprint positioning.

3.3 Construction of Hybrid Positioning System

At present, all types of positioning technologies have their specific application ranges. In positioning applications, different sub-regions often have different specific requirements for positioning accuracy, node density, etc. due to different user needs. If only one positioning method is used, it is often unable to meet application requirements and achieve reasonable optimization of resource allocation. In order to solve the above-mentioned problems, this article proposes the idea of hybrid indoor positioning, which combines the actual needs of users and selects different positioning technologies in different positioning fields according to the specific needs of users to overcome the shortcomings of using a single positioning technology. These two types of domains rely on domain evaluation algorithms to achieve coarse-grained determination of the domain to which unknown nodes belong, and to achieve seamless switching of different positioning algorithms. As shown in Figure 10.

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

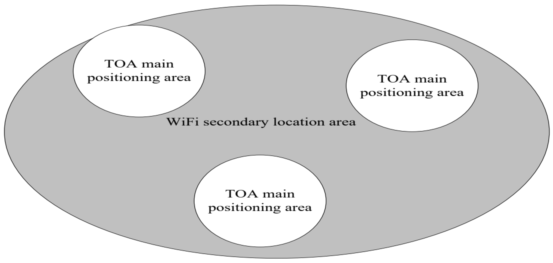


Figure 10: Basic principle of hybrid positioning system

(1) Positioning and mixed scheme design

According to the staff's activity area, the site can be divided into corridor area and indoor area. The space area is the main gathering area for people and goods, and it is also an important place to provide various location-related services. Therefore, anchor nodes are needed to provide high-precision location services. In the corridor area, the area is very large, and electromagnetic signals are greatly attenuated there, so communication jams are prone to occur. Therefore, the positioning of the corridor area places more emphasis on strong node communication capabilities, long signal range and low cost. Combining the above analysis of positioning requirements, this paper designs a hybrid TOA and WIFI system for multiple areas in the building. The system uses TOA positioning indoors with high accuracy. The corridor area uses the widely used WIFI anchor nodes in the building to achieve fingerprint positioning. The frame of this positioning system is shown in Figure 11.

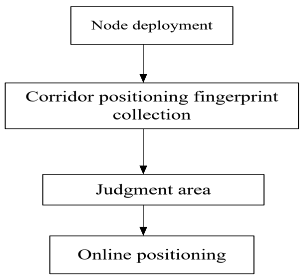


Figure 11: Framework diagram of the positioning algorithm flow

(2) Classification based on BP neural network

The division of the unknown node area must be considered based on two situations. Move from the corridor area to the indoor area and from the indoor area to the corridor area. Due to the obstruction of indoor doors and walls, indoor WIFI signals are greatly attenuated by the signals of public WIFI nodes distributed in the corridor area, while the WIFI signals of indoor users are amplified. Some of the results obtained are shown in Figure 12.

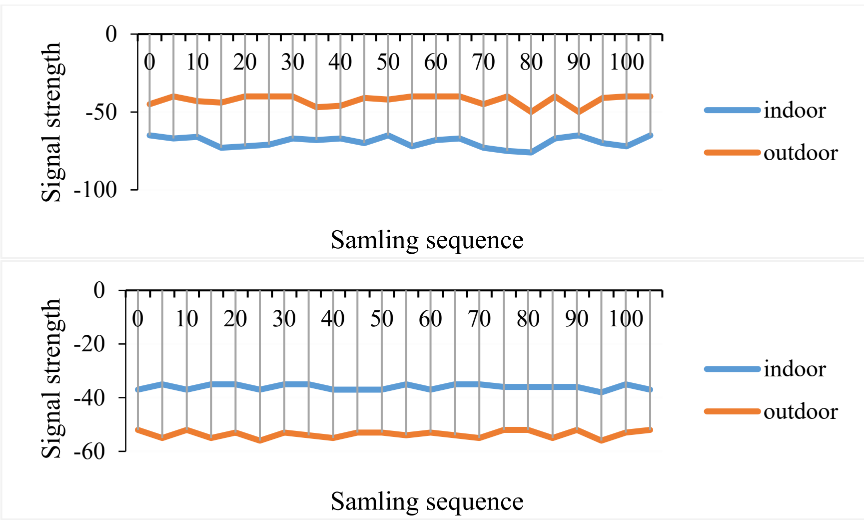


Figure 12: WiFi signal strength indoor and outdoor

From the comparison of Figure 12(1) and 12(2), it can be seen that compared with the outdoor

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

situation, the indoor public WIFI signal is weaker, and the user's WIFI signal is stronger. This is consistent with the above conclusion. The characteristic difference of the critical area between the external public WIFI is used to distinguish whether the unknown node is indoor or outdoor. The classification number of the BP neural network used to distinguish regional sub-areas in WIFI positioning is enhanced by adding the indoor area category of the space to be located in the original output area category, and the enhanced neural network is used. The study acquires and trains features to identify unknown node regions and corridor regions in interior space. This study uses the training results to realize the identification of corridor location and corridor moving space.

(3) Construction of experimental platform

1) Indoor positioning construction: In indoor positioning, this paper distributes four TOA ranging anchor nodes in the four corners of the room positioning area, and the unknown nodes are carried on the person. When personnel are located, the distance between each anchor node and the personnel is obtained by running the upper computer software on the tablet to calculate the position. The composition is shown in Figure 13:

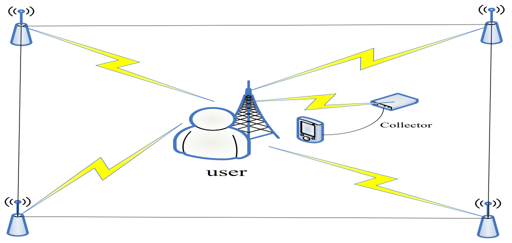


Figure 13: Indoor TOA positioning structure

2) Corridor positioning construction: In the corridor positioning, this article uses WIFI positioning, wireless sensors are used as positioning anchor nodes, and the selected users are used as auxiliary positioning anchor nodes. In the early stage, the signal strength of the two routers is manually collected by personnel, and the fingerprint positioning map and the rough map are drawn. Position the map and perform BP learning of coarse positioning data. The composition is shown in Figure 14:

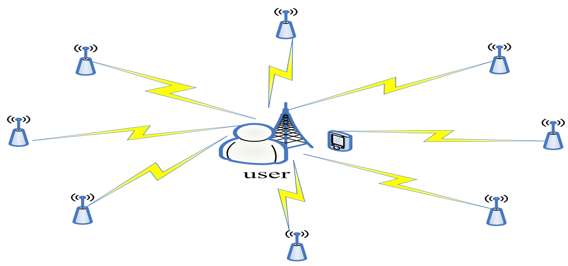


Figure 14: Principle of WiFi positioning structure in corridor

4. Comparative Experimental Analysis of Monitoring and Positioning Based on Wireless Sensors

4.1 Indoor Positioning Technology Based on Toa Ranging

Table 2: Mean positioning error of different algorithms

Area	Positioning error is mean			
	Least squares	Least Squares+Kalman	Least squares+Kalman+error fitting	Algorithm
1	1.6	1.6	0.5	0.3
2	3.2	3.2	0.9	0.3
3	3.2	3.2	0.8	0.2
4	2.7	2.7	1	0.3
5	1.7	1.7	0.5	0.2
6	2.7	2.7	0.8	0.3

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

Table 3: Positioning mean square error values of different algorithms

Area	Positioning error is mean			
	Least squares	Least Squares+Kalman	Least squares+Kalman+error fitting	Algorithm
1	0.5	0.1	0.02	0.02
2	0.6	0.2	0.1	0.06
3	0.7	0.2	0.08	0.02
4	0.6	0.3	0.12	0.1
5	0.5	0.2	0.08	0.05
6	0.6	0.2	0.1	0.1

(1) Fixed-point positioning experiment under line-of-sight environment: This paper simultaneously uses least square method, Kalman filter + least square method and Kalman filter + system error fitting correction + least square method to carry out positioning experiment, and record the corresponding experimental data. The experimental results are shown in Table 2 and Table 3:

From the data analysis of Table 2 and Table 3, it can be seen that when comparing the above four positioning algorithms, because the distance error is not corrected, the positioning error is the largest when the least squares positioning algorithm is directly applied. In the positioning algorithm of Kalman and least squares method, Kalman can only effectively suppress random errors and non-visible distance errors, but cannot suppress other system errors. Therefore, there will be no non-visible errors and positioning errors in line-of-sight positioning. The average value of is similar to the error of the least square method, and the average square error is significantly improved.

(2) Fixed-point positioning experiment in non-line-of-sight environment: Considering the actual indoor positioning environment, people walk randomly and perform fixed-point positioning for the position in Experiment 1:

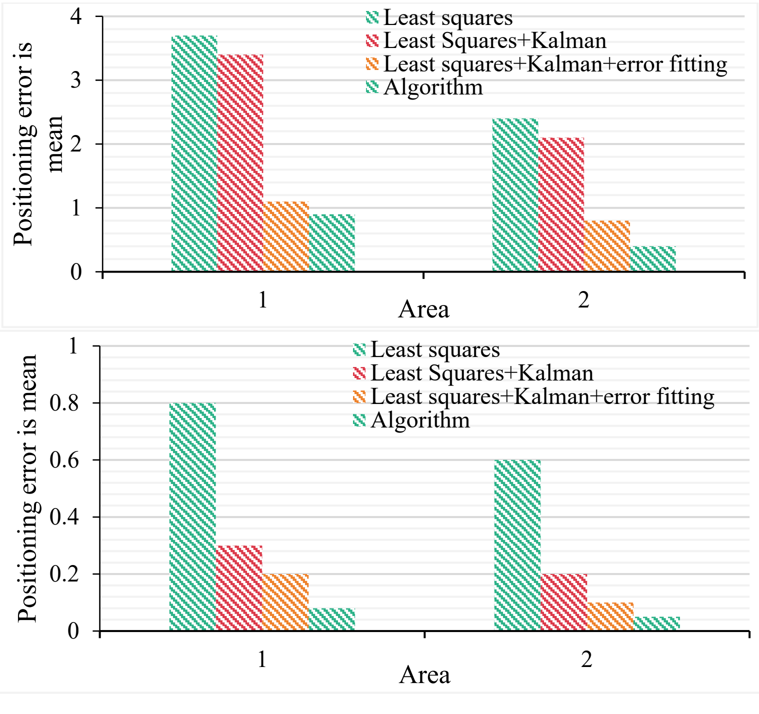


Figure 15: Performance indicators of the four positioning algorithms

It can be seen from Figure 15 that the noise in the non-visual environment causes the measurement distance of the anchor point to increase randomly, so the average error and mean square error of the four algorithms have increased compared with the values in Table 2 and Table 3, of which the smallest The positioning error and scatter of the square method are the largest, and the mean square error after Kalman filtering is much smaller than before filtering. It can be seen that Kalman filter can effectively suppress non-visual noise, but due to the existence of system error, the positioning error is still large; the use of system error fitting or the algorithm of this paper can effectively suppress the system error, but after the exponent, the algorithm of this paper Performance is better.

4.2 Location Fingerprint Positioning Technology Based on Wifi

(1) Corridor area area discrimination experiment

In order to test the effectiveness of the improved WIFI positioning algorithm in this work, a positioning experiment was carried out by locating sample points with known coordinates in the corridor and calculating the positioning error. The algorithm is compared with the traditional k-mean KNN algorithm, and the average error is calculated after each fixed point is found.

Table 4: Comparison of positioning effects of WiFi positioning algorithms

Sampling point	Positioning error is mean	
	Traditional KNN algorithm	Algorithm
1	2	1.7
2	2.8	2.3
3	4.3	1.8
4	2.5	2.3
5	2.9	0.9
6	2.7	1.6

As shown in Table 4, compared with the traditional k-mean+KNN algorithm, the algorithm in this paper can effectively suppress the impact of isolated fingerprint data in the k-mean classification result on the positioning, and effectively improve the positioning accuracy.

4.3 Experimental Analysis of Hybrid Positioning System

In order to verify the effectiveness of the range discrimination algorithm in the WIFI positioning in the corridor, the correct experimental position discrimination numbers were counted, and the experimental results are shown in Table 5.

Table 5: Probability of Regional Discrimination

Area	Correct number	Partially correct number	Number of errors
1	87	13	0
2	82	15	3
3	90	6	4
4(Outdoor)	95	0	5
5(Outdoor)	84	14	2
6(Outdoor)	91	8	1

It can be seen from Table 5 that in the identification of the corridor area, the accuracy rate of the completely correct corridor area type judgment can reach 87%, and the accuracy rate of the area type judgment can reach 90%. When a partially correct corridor area judgment occurs, it indicates that the sub-area of the fingerprint database where the unknown node is actually located is inconsistent with the area discrimination result, resulting in a decrease in accuracy; when a completely wrong corridor area judgment occurs, the indoor TOA positioning is activated and the positioning fails.

5. Conclusions

At present, wireless sensor network technology has been widely used in the field of building intelligence, and indoor positioning technology provides a technical foundation for realizing building intelligence. This paper analyzes and studies the positioning requirements of intelligent buildings, and puts forward the concept of hybrid positioning, that is, adopting multiple positioning technologies according to demand. The technical solutions of TOA indoor positioning and WIFI fingerprint indoor positioning in the building can better meet the positioning requirements of different areas and different precisions in the building, and have a higher cost performance. By setting the penalty function of the system error estimation range, the feasible range of the scheme is further reduced, the system error is corrected, and the positioning accuracy is improved. It is verified by experiments that the combination of the above two algorithms can significantly suppress the measurement error of indoor TOA positioning, and significantly improve the positioning accuracy. Secondly, in the context of corridor area positioning, the fingerprint-based WIFI positioning technology is studied, and based on the model that analyzes the range signal strength and RSSI characteristics in the actual environment, a smoothing strategy based on Kalman filter is proposed. On the other hand, for the K-means cluster classification

ISSN 2616-5767 Vol.7, Issue 3: 116-128, DOI: 10.25236/AJETS.2024.070317

problem of the fingerprint library sensitive to outliers in fingerprint matching, the similarity between the matched fingerprint and the measured RSSI vector is used as the K-nearest neighbor weight of the positioning calculation algorithm to form Weighted K-nearest neighbor fingerprint matching and location algorithm. Experiments show that Kalman filter has a good smoothing effect on RSSI values, and the accuracy of the regional discrimination strategy is very high. The hybrid measurement system designed in this paper is feasible.

References

[1] Peng Y, Al-Hazemi F, Boutaba R, et al. Enhancing Energy Efficiency via Cooperative MIMO in Wireless Sensor Networks: State of the Art and Future Research Directions. IEEE Communications Magazine, 2017, 55(11): 47-53.
[2] Wang T, Peng Z, Wen S, et al. A Survey of Fog Computing in Wireless Sensor Networks: Concepts, Frameworks, Applications and Issues. Ad Hoc & Sensor Wireless Networks, 2019, 44(1-2): 109-130.
[3] Shim K A. A Survey of Public-Key Cryptographic Primitives in Wireless Sensor Networks. IEEE Communications Surveys & Tutorials, 2017, 18(1): 577-601.
[4] Luo J, Hu J, D Wu, et al. Opportunistic Routing Algorithm for Relay Node Selection in Wireless Sensor Networks. IEEE Transactions on Industrial Informatics, 2017, 11(1): 112-121.
[5] Remah A, Khaled E. Performance and Challenges of Service-Oriented Architecture for Wireless Sensor Networks. Sensors, 2017, 20 (536): 536-575.
[6] Kunz T, Tatham B. Localization in Wireless Sensor Networks and Anchor Placement. Journal of Sensor & Actuator Networks, 2018, 1(1): 36-58.
[7] Havinga P, Meratnia N, Bahrepour M. Artificial intelligence based event detection in wireless sensor networks. University of Twente, 2017, 85(6): 1553-62.
[8] Ying Z, Wang J, Han D, et al. Fuzzy-Logic Based Distributed Energy-Efficient Clustering Algorithm for Wireless Sensor Networks. Sensors, 2017, 17(7): 1554.
[9] Zhang H, Hong X, Cheng J, et al. Secure Resource Allocation for OFDMA Two-Way Relay Wireless Sensor Networks Without and With Cooperative Jamming. IEEE Transactions on Industrial Informatics, 2017, 12(5): 1714-1725.
[10] Dong M, Ota K, Liu A. RMER: Reliable and Energy-Efficient Data Collection for Large-Scale Wireless Sensor Networks. IEEE Internet of Things Journal, 2017, 3(4): 511-519.
[11] Han G, Jiang J, Zhang C, et al. A Survey on Mobile Anchor Node Assisted Localization in Wireless Sensor Networks. IEEE Communications Surveys & Tutorials, 2017, 18(3): 2220-2243.
[12] Deng Y, Wang L, Elkashlan M, et al. Physical Layer Security in Three-Tier Wireless Sensor Networks: A Stochastic Geometry Approach. IEEE Transactions on Information Forensics and Security, 2017, 11(6): 1128-1138.
[13] Hu Y, Dong M, Ota K, et al. Mobile Target Detection in Wireless Sensor Networks With Adjustable Sensing Frequency. IEEE Systems Journal, 2017, 10(3): 1160-1171.
[14] Fei Z, Li B, Yang S, et al. A Survey of Multi-Objective Optimization in Wireless Sensor Networks: Metrics, Algorithms, and Open Problems. IEEE Communications Surveys & Tutorials, 2017, 19(1): 550-586.
[15] Boselin P, Sakkthi V, Babu A, et al. Mobility Assisted Dynamic Routing for Mobile Wireless Sensor Networks. Social Science Electronic Publishing, 2017, 3(1): 9-19.
[16] Seo S H, Won J, Sultana S, et al. Effective Key Management in Dynamic Wireless Sensor Networks. IEEE Transactions on Information Forensics and Security, 2017, 10(2): 371-383.