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Research Article

Research on Indoor Environment Positioning System considering Multisensor in the Multi-Information Data Fusion

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Outdoor positioning can often achieve accurate positioning according to GPS and mobile phone signaling, while indoor positioning is difficult to meet the needs of practical application due to the limitations of satellite reception. In order to effectively solve the problem of large error in the individual positioning strategy in the indoor environment, this paper applies multisensor in the multisource information fusion indoor positioning system. By using the positioning results of multiple sensors to limit the range of geomagnetic matching for combined matching, the matching error can be effectively reduced. Then, the global optimal value of indoor network is calculated by using the multi-information data fusion algorithm, which can optimize the initial value and threshold of the multi-information data fusion algorithm, improve the network accuracy as much as possible, and accelerate the convergence speed at the same time. After completing the optimization processing, the indoor network can obtain the combined positioning and predicted positioning results, so as to facilitate the fusion training to the actual position coordinates, and finally obtain the optimal positioning results. The simulation results show that the mean square error predicted by the multi-information data fusion algorithm calculated by the multi-information data fusion algorithm can be effectively reduced by 76%, and the fusion positioning accuracy can be improved by 48% compared with the accuracy of a single positioning strategy. The method proposed in this paper effectively improves the positioning accuracy, indicating that the positioning performance is better.

1. Introduction

With the effective development and improvement of Internet technology and satellite technology, experts within the industry have conducted more in-depth and intensive research on human activities [1, 2]. Robots appear in more and more fields, and such intelligent robots are often introduced into the production of various enterprises, especially in cluster production [3, 4]. In the specific industrialized and process-oriented robot production process, the smooth completion of the task can only be ensured by ensuring safe, effective, and collaborative work [5, 6]. Typically, in the logistics industry, it is important to make the corresponding task scheduling more accurate, put in accurately, and accurately capture the location [7, 8]. Wi-Fi, GPS/BeiDou/GNSS and other methods are often used for the traditional positioning methods to achieve specific navigation and positioning, but it should be noted that satellite signals are often affected by the surrounding environment and buildings. In several cases, there may even be a loss of signal and the result that positioning cannot be achieved. Therefore, the traditional GPS satellite type positioning cannot be well applied to indoor environment positioning [9, 10]. At present, most of the indoor positioning of robots often uses fusion sensors such as laser radar technique, mileage recording, and inertial measurement unit technology to achieve positioning. Different from the traditional GPS positioning method, this sensor-based positioning is not disturbed by the environment, and there is no need to worry about the weakening of satellite signals and can effectively achieve specific positioning indoors [11, 12]. The specific indoor positioning usually includes two methods: one is to achieve specific positioning based on basic image processing, and the other is to achieve positioning by effective data information fusion for multiple sensors. In addition, it should be noted that different methods require different sensors, such as RFID, Wi-Fi, and pedometer sensors, but these sensors are also different due to different materials, equipment manufacturing, technology, and structure, which often lead to the unstable collection of the data [9, 13]. The mileage pedometer mainly relies on the specific motor installed to realize the coding work and does not need the external information of the sensor to realize the specific positioning, but this method often causes systematic and random errors, which will cause the decline of the estimation accuracy of the pose. Inertial measurement unit technology positioning needs to achieve positioning after the specific intelligent machine moves, but the positioning accuracy of this method is not enough, and offsets often occur. Relatively speaking, the accuracy of laser radar positioning is relatively high, but this requires a relatively clear environment. If the laser information is blocked to a certain extent, the scanned information will not match the corresponding map information, thus resulting in inaccurate positioning. For UWB positioning technology, it is a relative way to provide absolute position, but if there are many obstacles in the room, the relative accuracy is low. If a single sensor is used for positioning, however, due to the limitation of their respective perception capabilities, the accuracy and precision of positioning are insufficient. Therefore, it is necessary to perform fusion positioning of multiple sensors to improve the reliability of positioning [14]. Due to the rapid development of wireless communication technology and multisource data, multisource data are widely used in various fields as an emerging network technology. The flow of indoor multisource data, the daily multisource data high-performance scientific computing, the multisource data high-performance scientific computing industry, and the monitoring of real-time information of multisource data is becoming more and more important. By setting up real-time positioning and real-time monitoring on multisource data high-performance scientific computing, we can perceive various types of data information in multisource data high-performance scientific computing, use multiple sensor terminals to realize monitoring and management, and complete the real-time monitoring and management of high-performance scientific computing. Because the nodes corresponding to the distributed indoor flow have the characteristics of high mobility and large network scale, higher requirements are put forward for the reliability, stability, and security of the real-time positioning and real-time monitoring system. Compared with the traditional methods, the positioning and real-time monitoring system based on multi-information data fusion algorithm needs to analyze the extracted multisource data information, which can complete the high-performance scientific calculation and positioning of multisource data, resulting in simple equipment structure, low cost, and convenient maintenance. It has gradually become the continuous development trend of real-time positioning and real-time monitoring system in intelligent room.

In view of these needs and deficiencies, this paper attempts to introduce Kalman filtering to integrate multisensor data and integrates mileage pedometer, inertial measurement unit technology, and laser radar information technology to achieve specific indoor positioning analysis, and simulation experiments are used to verify and to improve the accuracy and reliability of indoor positioning.

1.1. Basic Theory and Related Information Fusion Technology

1.1.1. Relevant Basic Theories

(1) Fuzzy Logic Theory. For fuzzy logic theory, it is not a specific mathematical model; relatively speaking, the cost is low, the calculation is more convenient, and the operability is strong. During the specific construction and acquisition process, specific and detailed positioning analysis cannot be achieved. Therefore, the specific structure of fuzzy modeling cannot be specifically set according to specific comprehensive indicators.

(2) Bayesian Inference Method. Bayesian inference method has many relatively specific applications, such as parameter self-adaptation, structure self-adaptation, and other methods. This inference method requires the relative independence of data; therefore, it is difficult to construct the system. In a specific system, there are specific rules of increase and decrease, and this method needs to recalculate the specific probability to achieve the specific consistency and specific correlation of the system [15].

(3) Dempster–Shafer Reasoning. For the inference method, its main feature is to properly deal with undetermined problems, especially for conditional probability, and it can realize a specific posterior method, but the disadvantage of this method is that its framework is relatively limited; meanwhile, conflicting combinations are prone to exist [16, 17].

(4) BLE Positioning. For BLE positioning, it mainly solves the communication problem between mobile devices and fixed-location devices through Bluetooth technology. General communication equipment often includes two parts: one is the specific gravity equipment part, and the other is the specific peripheral equipment part. Therefore, in this case, the peripheral device will scan through the specific center of gravity device and use the broadcast in the peripheral device to contain specific identification information and the specific content of the broadcast frame, so as to realize the distance judgment and analysis between the specific device and the center of gravity device [18, 19]. Through the actual establishment of training samples, the specific position and relative distance are analyzed, and the specific instructions for the next step are realized.

The functions of the parallel distributed multisensor information fusion system can be intuitively represented abstractly in Figure 1.

1.2. Structural Relation of Entropy of Information Fusion System. The concept of entropy comes from thermodynamics and can be calculated specifically by the following formula:

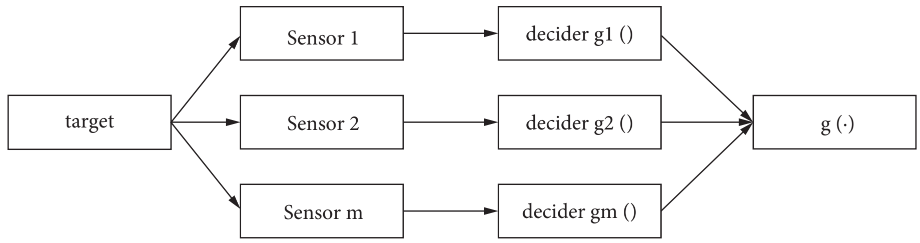

Figure 1: Functional block diagram of parallel distributed multisensor detection and decision fusion system.

$$H(p_1, p_2, \cdots p_n) = -\sum_i p_i \ln(p_i). \quad (1)$$

Here, X_k is the probability of the corresponding event.

Definition: $H(K)$, $H(K\text{-}1)$ is the fusion entropy; $I(k)$ is the amount of mutual information, under the condition of information correlation, $I(k) > 0$, specifically, as shown in following formulas:

$$H(k) = -\sum_i \left[p\left(y|Z^k\right)\ln\, p\left(y|Z^k\right)\right], \quad (2)$$

$$H(k-1) = -\sum_i \left[p\left(y|Z^{k-1}\right)\ln\, p\left(y|Z^{k-1}\right)\right], \quad (3)$$

$$I(k) = -\sum_i \left[p(y|z_i)\ln\frac{p(z_i|y)}{p(z_i)}\right]. \quad (4)$$

Changes are made on the basis of formula (2), formula (3), and formula (4), and the specific calculation can be obtained as follows:

$$H(k) = H(k-1) - I(k). \quad (5)$$

For information fusion in space, formula (5) represents the structural relationship between the entropy of the fusion system and its subfusion systems.

The first step is to analyze the threat factor data set and effectively classify it [20, 21].

We suppose that the strike targets can be divided into n categories, and the following sets are defined:

(1) All target objects are initialized, and the specific target object set is represented by the corresponding data set $X = \{x_1, x_2, \cdots, x_n\}$.

(2) Threat level classification set reflects the possible threat level of each target:

D = {d1, d2, d3, d4, d5, d6} = {The greatest threat, the very great threat, the second greatest threat, the greater threat, the general threat, the low threat}.

(3) Threat factor set attributes reflect the impact of air strike targets on threat estimation:

$A = \{a_1, a_2, \cdots, a_t\}$, $a_i\,(i = 1, 2, \cdots, t)$ reflect the attributes of different targets that affect the degree of threat, such as target types, mission attempts, interference capabilities, hit capabilities, and navigation elements.

The second step is to construct the mathematical model of fuzzy recognition based on the first step [4, 22].

For a certain target $x_i \in X$, $(i = 1, 2, \cdots, n)$, the threat factor set $A = \{a_1, a_2, \cdots, a_t\}$ of the target can be obtained through the sensor data, according to which the object x_i can be classified, which is a problem of pattern recognition.

For a finite set of target objects $X = \{x_1, x_2, \cdots, x_n\}$, $P = \{p_1, p_2, \cdots, p_n\}$ is the probability distribution over the set; for $\forall_i$, $p_i > 0$, and $\sum_{i=1}^n p_i = 1$. On the basis of formula (1), the probability distribution entropy can be calculated by the following formula:

$$H(p) = -\sum_{i=1}^{n} p_i \ln(p_i). \quad (6)$$

Let $f(k)\,(k = 1, 2, \cdots, m; m \le n)$ be the distribution function defined on $X = \{x_1, x_2, \cdots, x_n\}$, the mathematical expectation can be specifically calculated by the following formula :

$$E[f(k)] = \sum_{j=0}^{n} p_j \cdot f_j(k). \quad (7)$$

On the basis of formula (7), the probability distribution of a specific value needs to be solved. If the value of m is less than n, the relative probability distribution is not unique, which requires a selection criterion to determine the most reasonable probability distribution. When E[f(k)] is constrained to take a specific value, the distribution that maximizes the entropy should be selected. The result of pattern recognition can be calculated specifically by the following formula:

$$a_0 = \begin{cases} 0, & p(0|a_1, a_2, \cdots, a_t) > p(1|a_1, a_2, \cdots, a_t), \\ 1, & p(0|a_1, a_2, \cdots, a_t) < p(1|a_1, a_2, \cdots, a_t). \end{cases} \quad (8)$$

The solution that requires the maximum entropy distribution is equivalent to solving a conditional extremum, which is solved by the Lagrangian method. We define

$$G(p_i, \lambda_k) = -\sum_{i=1}^{n} p_i \ln(p_i) - \sum_{k=0}^{m} \lambda_k\left(\overline{f(k)} - E[f(k)]\right). \quad (9)$$

The necessary and sufficient conditions for the above formula to take the maximum value are as follows:

$$\frac{\partial G}{\partial p_i} = 0, \quad (i = 1, 2, \cdots, n) \text{ and } \frac{\partial G}{\partial \lambda_k} = 0, \quad (k = 1, 2, \cdots, m). \quad (10)$$

Then,

$$\ln p_i + 1 - \sum_{k=0}^{m} \lambda_k f_i(k) = 0, \text{and} \overline{f_i(k)} = E[f_i(k)]. \tag{11}$$

From this solution, the maximum entropy distribution $f_i(k)$ can be obtained, so that the classification to which the object should belong can be obtained, to achieve the purpose of pattern recognition.

1.3. System Analysis of Mobile Positioning Technology. In the specific GPS positioning process, due to the limitation of the reception of satellite signals, there may be signal loss and instability. Therefore, in this case, the use of Bluetooth technology for indoor positioning of logistics intelligent robots is relatively reliable and precise. Since the logistics intelligent robot selected is wheeled, its specific moving distance can be obtained through the specific wheel speed and the corresponding radius. Sensors are installed on the left and right sides of the intelligent robot. During the specific travel process, the sensors collect the corresponding rotational speed and position data to calculate the speed of the wheels, and then transmit the corresponding rotational speed data to the server for fusion through the corresponding electronic compass data, to achieve the measurement and calculation of the robot coordinates and position in the moving distance [23, 24]. In addition, the analysis of sensor data is required to analyze the specific model of Bluetooth positioning and realize the specific calculation of indoor position by classifying and inputting the data. On the server side, two methods can be integrated to realize the information analysis of the environmental sensors and further obtain the position of the intelligent robot accurately.

Under normal circumstances, intelligent robots are often divided into three specific movements in three directions, namely, going straight, turning left, and turning right, specifically as shown in Figure 2.

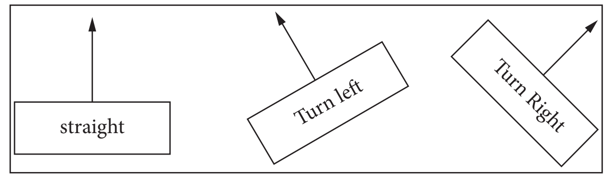

Figure 2: Steering of the robot.

Among them, the left and right photoelectric sensor signals are marked as Fl and Fr, respectively, and the motion state of the logistics robot is also divided into three relationships for the sensing signals: Fl = Fr, Fl > Fr, and Fl < Fr.

Threat assessment is to estimate whether the target is close enough to a fire unit or defended object, determine whether the target poses a threat to it and the size of the threat, and then rank the targets according to the size of the threat. The evaluation steps are shown in Figure 2.

Step instructions are as follows:

(1) Apply the maximum entropy method of pattern recognition to classify striking targets.

(2) Determine the target threat level according to the results of ① and the knowledge base of the established threat level classification set. The basic form of the rules in the knowledge base is as follows:

<rule ≥ IF < antecedent > THEN < conclusion > (OR<action>).

The meaning of the whole equation produced is that if the antecedent is satisfied, then the conclusion can be obtained or the striking specified action can be implemented. Specific rule examples are as follows:

<Rule I ≥ IF < Target Classification II "Tactical Ballistic Missiles"> THEN < maximum Threat>;

<Rule II ≥ IF < Target Classification = "air-to-ground missiles, antiradiation missiles"> THEN < very great threat>;

<Rule III ≥ IF < Target Classification II "Cruise Missiles, stealth plane, Large Bombers"> THEN < The second greatest threat>;

<Rule IV ≥ IF < Target Classification II "fighter plane, fighter-bomber plane, early warning command airplane"> THEN < The Greater Threat>;

<Rule V ≥ IF < Target Classification II "Small Plane, Helicopters, Reconnaissance Aircraft"> THEN < General Threat>;

<Rule VI ≥ IF < Target Classification II "Unidentified Machine, False Target, Bait"> THEN < Small threat>.

(3) Setting: among the n types of many striking targets, the threat level of the i ($i \in \{1, 2, \ldots, n\}$) target is denoted as $d(i)$, and the target has a threat factor set $A_i = \{a_1, a_2, \cdots, a_t\}$; the threat level of the j ($j \in \{1, 2, \ldots, t\}$) attribute of the i-th target is denoted as $e(i, j)$. Then, the threat degree D_i of the i-th target can be specifically calculated by the following formula:

$$D_i = \alpha \left[\mu_i \cdot d(i) + \sum_{j=1}^{t} \nu_{(j|i)} \cdot e(i, j) \right]. \tag{12}$$

In the formula, the specific weight of the target threat degree is represented by σ_Y, and the threat degree weight of a specific attribute is represented by $\nu_{(j|i)}$; the specific weight of the importance degree is represented by α.

On the basis of formula (12), the formula is transformed, specifically as shown in the following formula:

$$\mu_i + \sum_{j=1}^{t} \nu_{(j|i)} = 1, \alpha \in [0, 1]. \tag{13}$$

The algorithm based on BLE positioning technology and the algorithm of distance positioning can be used to accurately locate the robot. The specific calculation methods are shown in following formulas:

$$C_{pq} = 2\pi R \cdot Ps, \tag{14}$$

$$X \triangle t = C_{pq} \cdot \cos\theta, \tag{15}$$

$$Y\triangle t = C_{pq} \cdot \sin\theta, \tag{16}$$

$$X_p = XA_j + X\triangle t(p-1) + X\triangle t, \tag{17}$$

$$Y_q = YA_j + \cdots + Y\triangle t(q-1) + Y\triangle t_q. \tag{18}$$

When a specific intelligent robot completes a series of sorting and transfer tasks, it realizes the transformation and analysis of specific positions; that is, it can complete processes such as warehouse, path, and sorting. First, we start from the logistics warehouse to find the corresponding goods to be transshipped. After finding the goods, we send the goods to the specific sorting area for analysis and then return to the specific warehouse for the analysis of next task. When the logistics warehouse is set as the starting point of the intelligent robot, the initial position can be set to [0,0]. Meanwhile, we integrate the photoelectric sensor with the electronic compass accordingly, analyze and calculate the position of the intelligent logistics robot at a specific moment, use the current position coordinates as the input value of the indoor classification model, and use the nearest neighbor algorithm to obtain and analyze the best position of the logistics robot.

The specific indoor positioning algorithm of the logistics robot mainly includes two specific parts, namely, the offline machine learning part and the online location testing part. First of all, it is necessary to set up and learn according to the specific position of the robot, and build a specific overall classification model. This classification model needs to integrate two numerical models of indoor positioning and distance positioning. Firstly, the corresponding data sets are established by using various data obtained by Bluetooth sensors, photoelectric sensors, and electronic compass sensors, and specific models and algorithms are constructed for specific data sets. By constructing a specific location and database for specific mapping analysis, the specific area can be divided into several types. One is the collection of data location coordinates. In this way, the nearest neighbor algorithm can be used to obtain the specific relative position, so as to construct the mapping relationship model of the two. The online location test needs to be implemented from multiple aspects. On the one hand, the input data of data modeling are analyzed by using Bluetooth data to obtain the location of the intelligent robot at a specific time; on the other hand, according to the relative coordinate position of the specific distance-classified model and the specific robot, the specific logistics robot positioning is obtained; finally, the data results are integrated for specific analysis, comprehensive decision-making analysis is carried out through the integrated control unit, and corresponding services are output, to obtain the final indoor positioning, specifically as shown in Figure 3.

The so-called positioning information is actually the information parameters of the shared intelligent robot, and a fixed analysis is carried out according to the actual specific

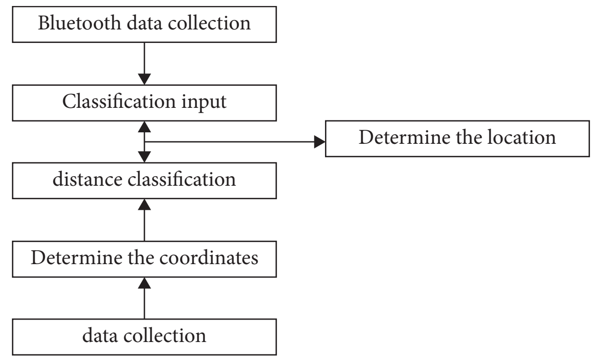

Figure 3: Data collection process.

collected relevant parameter data to realize decision support. When the logistics robot detects the corresponding destination, it can perform specific operation control according to the control unit, prompting the intelligent robot what the next operation and step are until the transfer task is completed and the control of the operating system is realized. When the robot completes the specific work and returns to the origin position of the logistics warehouse, the corresponding system will record the previous task environment and information. After the record is completed, it will be specifically cleared and wait for the next specific task of the intelligent robot.

The specific multisensor fusion positioning system mainly includes a positioning system, a mobile intelligent robot platform, and a computer, specifically as shown in Figure 4.

1.4. Indoor Environment Positioning Method. The multisensor fusion positioning process framework is shown in Figure 5.

As shown in Figure 5, the whole framework first uses the extended Kalman filter algorithm to perform data fusion of multisensors to realize data fusion of odometer pedometer, IMU, and BLE positioning information. Among them, EKF includes prediction step and update step. On this basis, the AMCL algorithm is used to analyze the laser radar positioning data, and the specific map matching update analysis is realized.

In accordance with the multi-information data fusion indoor environment positioning method and the basic principle of relative altimetry being adopted, the results of indoor positioning can be obtained based on the multi-information data fusion algorithm. With regard to the height measured by the sensors, the accurate positioning of the indoor environment can be completed. However, there are also errors in the results calculated by using the algorithm proposed in this paper. For the purpose of improving the accuracy of positioning, the process of the algorithm is optimized in this paper, and the multi-information data fusion process obtained after optimization is shown in Figure 6.

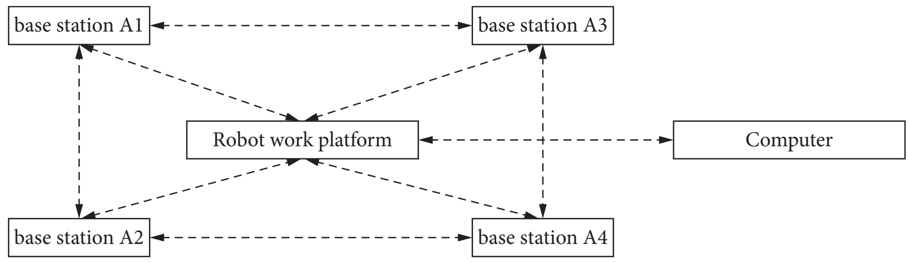

Figure 4: Composition of the positioning system.

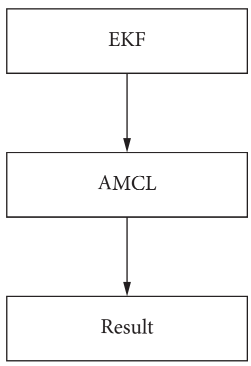

Figure 5: Flow chart of fusion positioning.

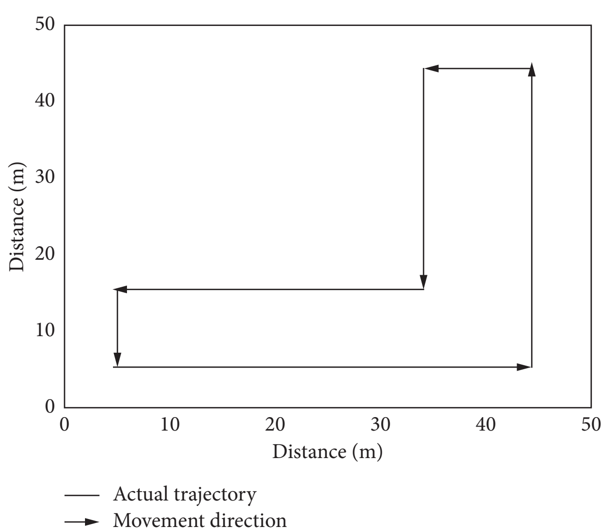

Figure 6: Multi-information data fusion process.

The process of multi-information data fusion is described as the following:

The state vector of multi-information data acquisition by the sensor can be represented as follows:

$$X = [\,X \;\; Y \;\; SL \;\; \psi \;\; H\,]. \tag{19}$$

In the above expressions, X and Y are used to stand for the coordinate values corresponding to the carrier in the data fusion coordinate system; SL stands for the step size being calculated; Ψ stands for the acquisition angle of sensor data; and H stands for the height.

The state expression for the sensor multi-information data acquisition is as follows:

$$\begin{cases} X_k = X_{k-1} + SL_k \cdot \cos(\psi_k) + W_X, \\ Y_k = Y_{K-1} + SL_k \cdot \sin(\psi_k) + W_Y, \\ SL_k = SL_{k-1} + W_{SL,} \\ \psi_k = \psi_{k-1} + W_\psi, \\ H_k = H_{k-1} + W_H. \end{cases} \tag{20}$$

The above expression is a nonlinear equation, which can be obtained by linearization processing:

$$X_k = \Phi_k X_{k-1} + W_k. \tag{21}$$

In the above expression, X_k is used to stand for the state vector of data information at the moment tk,φ_k stands for the transfer matrix of the state, and $W_k$stands for the noise vector of the fusion process. Thus, the state transfer matrix can be expressed as follows:

The state transfer matrix expression is as follows:

$$\Phi_k \approx \frac{\partial f}{\partial X}\Big|_{X=\overline{X}_k} = \begin{bmatrix} 1 & 0 & \cos\psi & -SL\cdot\sin\psi & 0 \\ 0 & 1 & \sin\psi & SL\cdot\cos\psi & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{X=\overline{X}_k}. \tag{22}$$

The observation vector can be expressed as follows:

$$L = [\,SL \;\; \psi \;\; H\,]. \tag{23}$$

The observation equation can be expressed as follows:

$$\begin{cases} SL_{P\,DR} = SL_k + V_{SL}, \\ \psi_{P\,DR} = \psi_k + V_\psi, \\ H_{P\,DR} = H_k + V_H. \end{cases} \tag{24}$$

Thus, it can be observed that the observation equation used has the linear characteristics and does not require linearization processing. Hence, the expression for the matrix designed can be obtained as follows:

$$B_k = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{25}$$

It is assumed that the state noise covariance matrix expression is as follows:

$$\Sigma_{W_k} = \begin{bmatrix} \sigma_X^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_Y^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{SL}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_\psi^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_H^2 \end{bmatrix}, \quad (26)$$

where $\sigma_X = \sigma_Y = 1\,\mathrm{m}$, $\sigma_{SL} = 0.03\,\mathrm{m}$, $\sigma_\psi = 0.5\,\mathrm{rad}$, and $\sigma_H = 0.5\,\mathrm{m}$.

The covariance matrix corresponding to the observation vector can be expressed as follows:

$$\Sigma_k = \begin{bmatrix} \sigma_{SL}^2 & 0 & 0 \\ 0 & \sigma_\psi^2 & 0 \\ 0 & 0 & \sigma_H^2 \end{bmatrix}. \quad (27)$$

1.5. Analysis of Experiment and Results. In this paper, for the purpose of testing the practicality of the multi-information data fusion indoor environment positioning system, simulation software is used to carry out simulation and testing. In a square area with a length of 50 cm, the nodes are moved along the arrows in a counterclockwise direction according to the simulated route, as shown in Figure 7. The moving speed of the node is 1 m/s, the time interval during the moving process is set to 0.5 s, and the moving position is stacked in an uninterrupted manner and monitored.

Compared with the other positioning methods, the positioning trajectory obtained based on the proposed method is smoother and closer to the reference trajectory, which suggests that the multisensor fusion positioning method put forward in this paper can achieve relatively high positioning accuracy and stability. The details are shown in Table 1.

The accuracy of positioning is calculated based on the multi-information data fusion algorithm, with the expression as follows:

$$\delta = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_0)^2}. \quad (28)$$

1.5.1. Non-Line-of-Sight Error. As shown in Figure 8, in this simulation experiment, the relationship between the LOS error value and RMSE is mainly studied, and the noise obeys the Gaussian distribution. From the results, with the increase of μ_N, the RMSE value of all algorithms increases, but the multisensor fusion positioning method (MSNIMA algorithm) in this paper has more obvious advantages and higher positioning accuracy.

As shown in Figure 9, this result shows that when the LOS error value is 2, the measurement obtained by noise follows a Gaussian distribution and the effect of non-line-of-sight error variance on RMSE. The multisensor fusion localization method (MSNIMA algorithm) has the best localization effect.

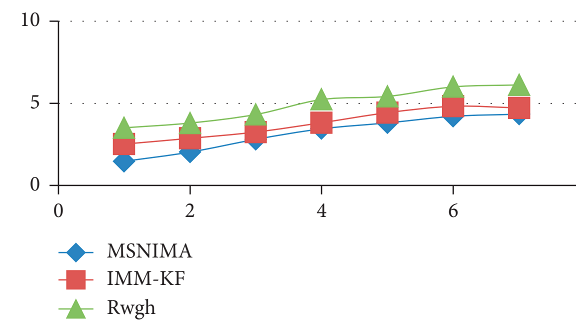

Figure 7: Simulation route for the indoor environment positioning.

Table 1: Accuracy of various positioning methods/m.

Accuracy of positioning in different directions	X direction of the movement	Y direction of the movement
Length of the movement route	0.6345	0.5733
Single sensor	0.3255	0.0824
Odometer	0.2055	0.2833
Fusion of multiple sensors	0.0734	0.0987

1.5.2. The Non-Line-of-Sight Error Follows an Exponential Distribution. As shown in Figures 10 and 11, the positioning accuracy of the multisensor fusion positioning method (MSNIMA algorithm) is better than the other two algorithms, which has obvious advantages.

As shown in Figure 11, the multisensor fusion localization method (MSNIMA algorithm) proposed in this paper is robust and has high pointing accuracy.

1.5.3. The Non-Line-of-Sight Error Obeys a Uniform Distribution. The results between the maximum deviation coefficient $U_{\max}$ and the root mean square error are shown in Figures 12 and 13. With the increase of the maximum deviation sparseness, the three algorithms all show an increasing trend, while the multisensor fusion positioning method proposed in this paper (MSNIMA algorithm) has high positioning accuracy.

For a single sensor, the weighted averaging method is more practical, and for the actual system, it is more advantageous. Typical methods such as Kalman filtering can effectively solve the problem of image fusion, and fuzzy logic methods can also help the filtering method to improve the corresponding robustness. The fusion of precision can realize the limitations of Bayesian through specific wavelet transform methods, so as to achieve specific model improvement and use. The fusion of various methods and the integration of various data can effectively improve the performance of the algorithm and improve the accuracy of indoor positioning.

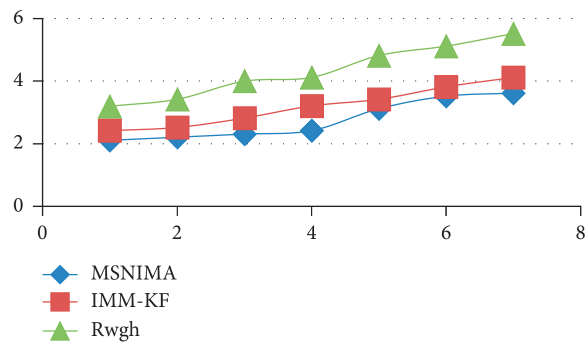

Figure 8: Relationship between the mean values of LOS error μ_N and RMSE.

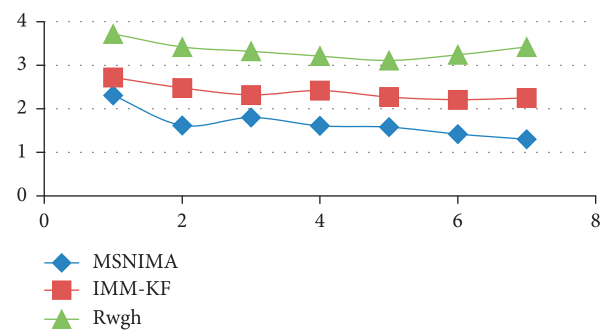

Figure 9: Relationship between LOS error variance σ_N^2 and RMSE.

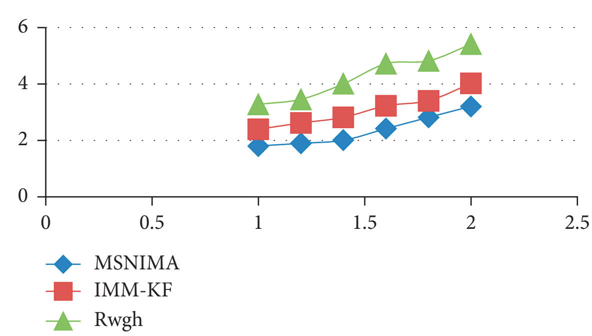

Figure 10: Relationship between parameters μ and RMSE.

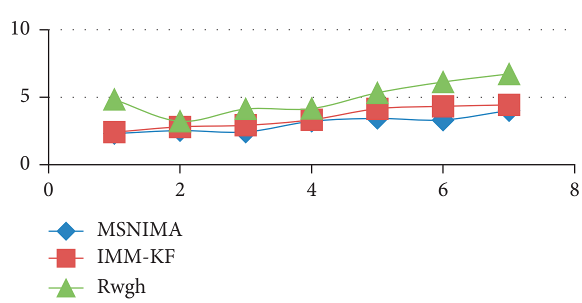

Figure 11: Relationship between standard deviation of measurement noise and RMSE.

In addition, multisensor fusion is a stationary and random relative process, which is mainly distributed through a linear structure. On the one hand, if the corresponding system performance needs to be improved, its algorithm needs to be improved to achieve nonlinear, nonstationary information fusion and improve the accuracy of indoor positioning.

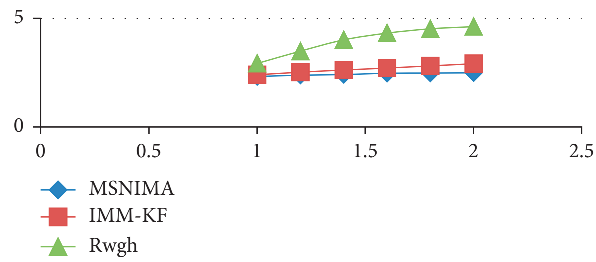

Figure 12: Relationship between $U_{\max}$ and RMSE.

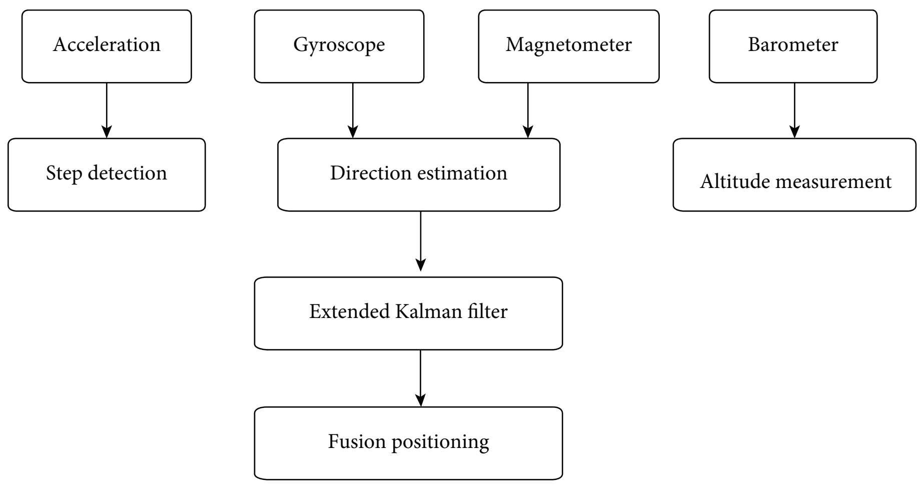

Figure 13: Relationship between standard deviation of measurement noise and RMSE.

2. Conclusions

In view of the large error of the current indoor single positioning method, it appears before using multisensor. In this paper, multiple sensors, geomagnetism, and multi-source data are used to extract the three indoor positioning features, which can be completed by mobile phone. We simplify the calculation and make the algorithm more complete. The multi-information data fusion algorithm is used to effectively solve the problem of slow convergence speed of neural network algorithm. The multisensor data fusion is carried out by relying on Kalman filter, and the odometer, inertial measurement unit technology, and lidar information technology are fused. Compared with the positioning method, the fusion positioning accuracy can be improved by 48%. The method proposed in this paper can use the sensors built in the mobile terminal, that is, the continuous and stable indoor positioning. If multiple sensor signals disappear, it can also continue to locate, indicating good scalability and fault tolerance. We achieve specific indoor positioning analysis. The simulation results show that the multisensor in the multi-information data fusion method is effective, can meet the actual needs, greatly improves the accuracy of indoor positioning, and has good stability at the same time.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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