

Research Article

Research on Software Design of Intelligent Sensor Robot System Based on Multidata Fusion

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Received 29 April 2021; Revised 22 May 2021; Accepted 1 June 2021; Published 3 July 2021

Academic Editor: Mu Zhou

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With the advent of robots combined with artificial intelligence, robots have become an indispensable part of production and life. Especially in recent years, the collaboration between humans and machines has become a research trend in the field of robotics, with high work efficiency and flexibility. The advantages of safety and stability make intelligent robots the best choice for the current industrial and service industries with high labor intensity and hazardous working environments. This paper is aimed at studying the software design of an intelligent sensor robot system based on multidata fusion. In this paper, through the needle robot's high precision requirements and the problem of fast response, a path design method based on the ant colony optimization (ACO) algorithm is proposed. Path planning is performed by intelligent robots for obstacle avoidance experiments, while global optimization is performed by the ant colony optimization (ACO) algorithm. For adaptive functions including obstacle reduction and path information length, the safest and shortest path is finally achieved through the ant colony optimization (ACO) algorithm. The experimental results show that using the ant colony optimization algorithm to perform simulation experiments and preprocessing operations on the data collected by the sensor can improve the accuracy and effectiveness of the data. The ant colony algorithm performs fusion and path planning, and on the basis of ensuring accuracy, it can speed up the convergence speed. Through the data analysis of obstacle avoidance experiments of intelligent robots, it can be concluded that it is very necessary for intelligent robots to install ultrasonic sensors and infrared sensors in obstacle avoidance, because the error between the test distance of the ultrasonic sensor and the infrared sensor and the actual distance is 0.001.

1. Introduction

1.1. Background of Topic Selection. Robots have become an indispensable part of production and life. Intelligent and standard robots combine mechanical design, computer software technology, advanced signal processing, communication engineering, materials science, computer vision, and other fields to form a complex, reliable, and intelligent system. The advancement and development of robotics fully proved the advancement of science and technology. In terms of industrial technology, military strength, skill level, and human survival services, the development of the country is closely related to the development of robotics. Therefore, the development and implementation of robot technology objectively represent the frontier of high-tech development, represent the country's technological development level, and represent the country's industrial automation and

high-tech level. The research, development, and rapid development of robots are an important step for the country to develop advanced technology, and it is also the only way to improve the country's comprehensive national strength.

1.2. Significance of the Research. In the control of intelligent sensor robots, sensors are the means to obtain external information, are the core of the overall perception of external information, and are responsible for receiving information about the external environment of the robot in real time so that the robot can make adjustments. Determine the work sequence and operation content according to changes in the natural working environment. It can more comprehensively reflect changes in the environment, so that correct decisions can be made and the accuracy, speed, and stability of the robot system can be ensured. However, because the information provided by a single sensor is too small to meet the

requirements of the entire robot, we urgently need a technology that can combine the information of many sensors at the same time to accurately guide the entire robot. Compared with single-sensor technology, the multisensor fusion control system has great characteristics. It can be used to enhance and improve the reliability of measurement data, expand the measurement range of the fusion system, and improve the robustness of the system. If some sensors have failed, you can quickly complete the reconfiguration and resume work. Multisensor data collection and calculation belong to the information fusion technology, which collect and calculate the data transmitted from different sensors to the processor, and combine the calculated data into a single interface description method to improve the adaptability of the robot. Multisensor data merging can describe the typical functions of the robot interface in more detail and ensure the safe and stable operation of the robot. Therefore, the development of multisensor fusion is becoming faster and faster, and it has become a research point in the field of robotics.

1.3. Relevant Work on the Software Design and Research of Intelligent Sensor Robot System Based on Multidata Fusion. This paper studies the software design of the intelligent sensor robot system based on multidata fusion, preprocessing the environmental information data collected from each sensor of the robot, processing and fusing the data collected from each sensor, and planning the movement path of the robot. Zhou et al. proposed the use of artificial potential fields to avoid obstacles on the mobile chassis. The target set by the host is defined as gravity, and obstacles in the environment are defined as repulsive forces. Based on this, artificial gravitation and repulsion models are constructed. According to the force function derived from the force field, the force of the robot in the working environment is obtained, and the speed of the robot is obtained to achieve the purpose of avoiding obstacles [1]. Zhang successfully implemented the high-stability and high-precision visual SLAM algorithm, completed the positioning based on the features of the matched image, and improved the stability of the mapping based on the advantages of scale-invariant feature transformation and Harris focus. SLAM's position and attitude estimation provides support. At the same time, the IMU data can be fused according to the Harris focusing method, and the motion of the robot can be predicted according to the posture estimation of the IMU, so that the quaternion can be used to solve the current position and posture of the robot. However, the use of the ant colony optimization algorithm can be better achieved [2]. Semmens et al. uses the extended Kalman filter method and the particle filter method to complete the test calculation of the signal with Gaussian noise distribution and uses the encoder as the sensor and the ultrasonic sensor as the condition estimation standard of the mobile device [3]. In this case, the particle filter requires a higher calculation cost, but the calculation time and calculation accuracy of the particle filter used for sensor fusion are stronger than those of the Kalman filter. However, by analyzing the challenging problems in the big data reaction, their research data volume is not large and the basis is insufficient.

1.4. Innovation Points of This Research

- (1) Multisensor information fusion technology can improve the reliability of measurement data, expand the measurement range of the fusion system, and improve the robustness of the system when some sensors fail. It can quickly complete reconfiguration and resume work
- (2) Through the ant colony optimization algorithm, the optimal path and faster convergence speed can be obtained during the obstacle avoidance process of the robot

2. Software Design and Research Method of Intelligent Sensor Robot System Based on Multidata Fusion

2.1. Goal of Multiple Data Fusion. Multidata fusion, also known as multisensor information fusion, has become a popular research field. It has been applied to many fields, such as navigation, robots, GPS positioning, and signal processing. In modern electronic warfare, it is difficult for the information provided by a single sensor to reach the target and carry out the requirements of tracking accuracy and state evaluation. The purpose of multisensor information fusion is to combine data from multiple sensors to measure environmental variables, reduce signal uncertainty, and improve measurement accuracy [4]. Therefore, they fuse different types of information at different levels for fusion, and the sensor can directly receive raw data or processed data [5]. In the fusion process, complex reasoning must be performed on this different and changing information to produce the effect of $1 + 1 > 2$, thereby improving the control efficiency of the controller [6].

2.2. Necessity of Multisensor Information Fusion. The collection of sensors and traditional robots that collect environmental information is a kind of intelligent robot. In order to make the robot have the same cognitive and judgment abilities as humans, it is necessary for the robot to perceive as much information about the environment as possible [7]. Intelligent robots based on multisensor information fusion can perceive the robot's environmental information and also enhance the robot's intelligent control capabilities [8, 9].

2.3. Features of Multisensor Information Fusion. Compared with single-sensor information fusion, multisensor information fusion has the following characteristics.

2.3.1. Good Stability. The performance of each sensor is complementary, and the information collected is not related to each other. The entire system receives complete information that cannot be received by any sensor [10]. Therefore, when one of the sensors fails, there will always be another sensor collecting environmental data as supplementary information, which will make the system less sensitive to interference caused by changes in the external environment, thereby improving the stability of the entire system [11].

2.3.2. High Reliability. Since information is obtained from multiple sensors, the possibility of data errors is greatly reduced. At the same time, the environmental information collected by many sensors also improves the system's understanding of the environment and significantly improves the overall reliability of the system [12].

2.3.3. Reduced Ambiguity of Information. When multiple sensors detect the same environmental target, more environmental information can be obtained, which greatly reduces the uncertainty of the detected environment [13].

2.3.4. The Overall Performance of the System Is Enhanced. In theory, it has been proven that sensing the environment or target through multiple sensors and fusing the received data using optimization methods will not reduce the overall performance of the system. In other words, the performance of a system based on multisensor information fusion is better than that of a single sensor. Generally, the performance of a multisensor information fusion system is better than that of a single-sensor system.

2.3.5. Expanded Space Coverage. Since different types of sensors have different capabilities for detecting environmental information, the distance and accuracy of detection are also different. By applying multiple different types of sensors to the same area at the same time, the space coverage can be greatly expanded [14].

2.4. Basic Principles of Multisensor Information Fusion. Multisensor fusion technology is a comprehensive and advanced decision-making process based on measurement results. In a multisensor system, since the information provided by different sensors may be different, they are mutually supportive or complementary [15]. Multisensor fusion technology utilizes multiple sensor resources to integrate redundant multisensor information in time and space, while eliminating errors or unreliable information, so as to obtain a consistent description or explanation of the object described. As a result, the sensor system has better performance than a system composed of various subsets [16].

2.5. Basic Methods of Multisensor Information Fusion

2.5.1. Random Method

- (1) *Weighted average method:* the weighted average method is usually suitable for dynamic environments with simple structure and low requirements for fusion accuracy. It is a simple and intuitive sensor data fusion algorithm. The weighted average method uses the weighted average of environmental data collected by sensors [17] and uses the final result as a fusion.
- (2) *Kalman filter method:* the Kalman filtering method is mainly used to merge real-time low-level data from multiple sensors. There are two information fusion methods based on the Kalman filter. The centralized Kalman filter directly integrates all the local observation equations to obtain the extended-dimensional

fusion observation equation, and then, the global optimal Kalman filter of the state equation is given [18]. However, the distributed Kalman filter uses the local weighted Kalman estimation to provide global optimal or global Kalman fusion [19]. Observation fusion technology can be broadly divided into core fusion technology, centralized fusion technology, and distributed fusion technology. The fusion observation method is the same as other fusion methods, and this variance observation fusion method is also referred to as the weighted observation fusion method. The weighted local observation equation can be used to obtain the weighted local observation equation, and then, the state equation can be used to obtain the Kalman filter fused with the weighted local observation [20]. However, the Kalman filter has two characteristic limitations: the system and the observation value must be nonlinear and in this case must be Gaussian. The actual environmental conditions are often more complicated, so we need to optimize the Kalman filter [21].

- (3) *Bayes estimation method:* the main difference between the Bayes estimation algorithm and traditional methods is whether to combine previous information and Bayes estimation model information. The parameter to be estimated is considered to be a random variable with some previous probability distribution constraints. Sample observation is actually a process in which the previous probability density is converted into a posterior probability distribution by calculation, so that the initial estimated parameters can be corrected from the useful sample information [18].

2.5.2. Artificial Intelligence Methods

- (1) *Neural network method:* the neural network has powerful self-learning, self-organization, and self-adaptation capabilities and can simulate complex nonlinear mapping. These neural network functions and powerful nonlinear processing capabilities can perfectly meet the requirements of multisensor data fusion processing [22]. In multiple sensor systems, each environmental information source can provide each environmental information because they have a certain degree of uncertainty, and these uncertainties are fused with other information. The process is actually a process derived from reasoning. The neural network determines its classification index based on the similarity of the samples accepted by the current system. This approach to decision-making is mainly reflected in the network weight and structure distribution [23]. At the same time, it also allows us to use a special neural network learning algorithm to obtain knowledge from the network and obtain the mechanism of inference uncertainty from the network. It uses the self-learning and reasoning functions of the neural network to perform multisensor data fusion.

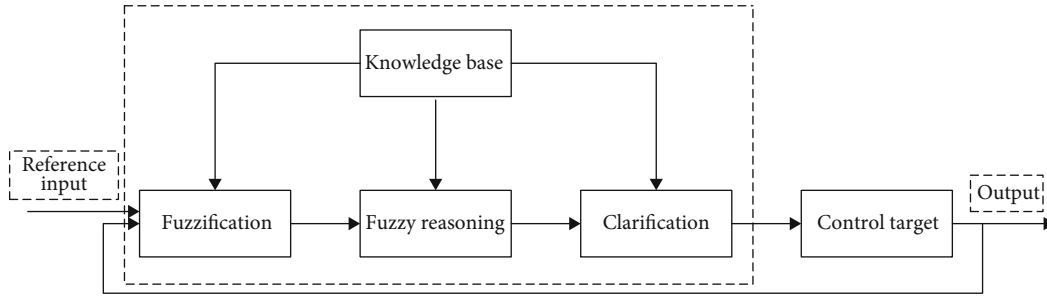


FIGURE 1: Block diagram of the fuzzy controller.

- (2) *Fuzzy logic theory algorithm*: the fuzzy logic theory algorithm is an algorithm for fuzzy general judgment, which simulates the thinking of the human brain. It uses some fuzzy rules to derive key performance indicators, but the key is to construct logical member functions and index functions [24]. In fuzzy reasoning, the subordinate rules are fuzzy rules. The fuzzy input set corresponds to the specific output set through specific functions. This calculation process is a fuzzy inference. In addition, using it with other different types of algorithms can significantly improve the efficiency of information fusion.

The structure diagram of the fuzzy controller is shown in Figure 1:

- (3) *Ant colony algorithm*: the ant colony algorithm is a new optimization algorithm inspired by the ant colony behavior in nature. Once the algorithm was proposed, it attracted widespread attention from scholars all over the world and successfully solved many combinatorial optimization problems [25].

The advantages of the ant colony algorithm are as follows: First, it is very robust, and simple modifications to the algorithm can be used to solve other problems. Second, the ant colony algorithm can be combined with some other algorithms for calculation, which can improve the calculation performance of the ant colony algorithm. The flow chart of the ant colony algorithm is shown in Figure 2.

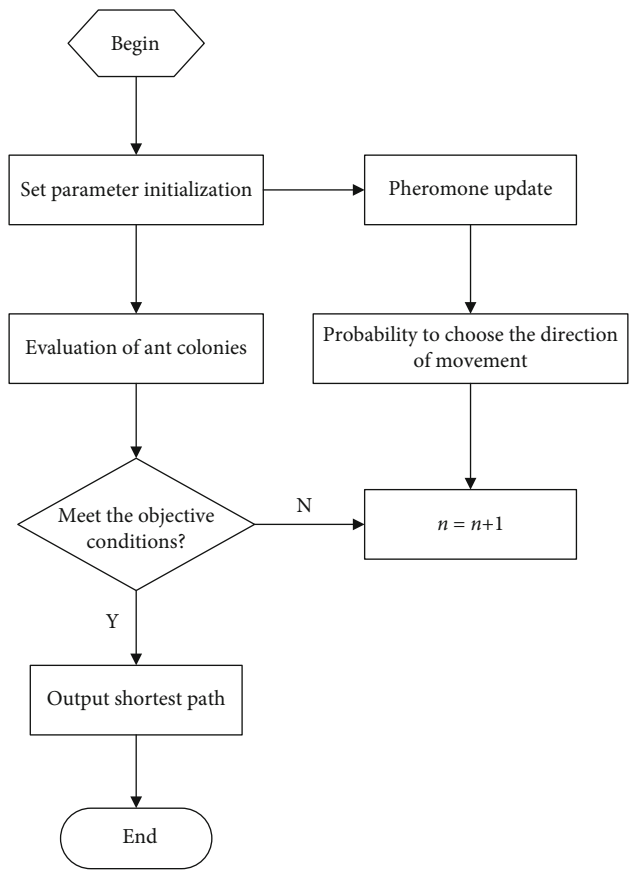


FIGURE 2: Ant colony algorithm flow chart.

2.6. Comparison of Multisensor Information Fusion Methods

- (1) The weighted average method is suitable for low-level data fusion in a dynamic operating environment. The advantage of this method is that there is less information loss and the initial data can be easily merged. The disadvantage is that a suitable mathematical model must be found, and the scope of application is relatively limited.
- (2) Kalman filtering method is suitable for low-level data fusion in a dynamic operating environment. This information is expressed as a probability distribution with Gaussian noise uncertainty. The advantage is that the amount of information transmitted by the data will not be lost, and the initial data can be easily integrated. The disadvantage is that it needs to build a

more accurate mathematical model or know the statistical properties, which limits the scope of application.

- (3) The Bayes estimation method is suitable for advanced data fusion in a static environment. It is also a way of representing information, which has an unknown probability distribution of Gaussian noise. The advantage is that the theoretical foundation is well supported, so it is easy to understand and implement. The disadvantage is that it is difficult to obtain prior knowledge, which limits its widespread use.
- (4) The neural network method can run on the bottom data of the dynamic environment or the top data of

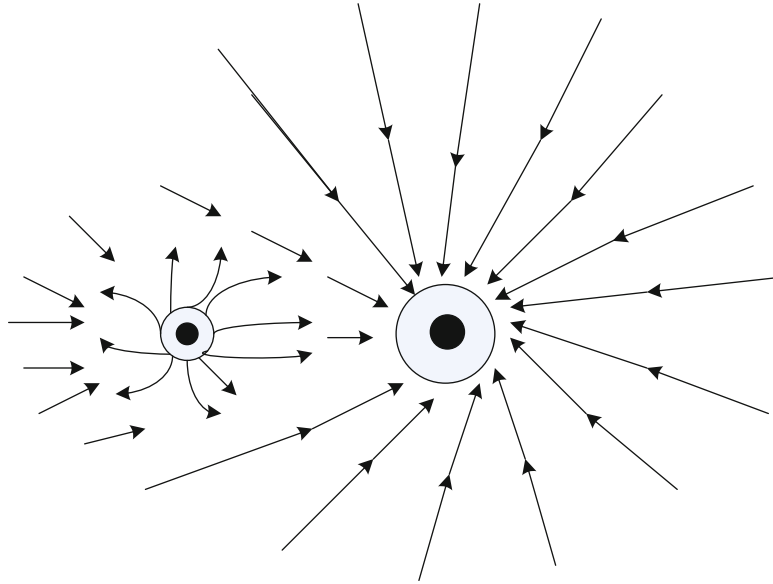


FIGURE 3: Schematic diagram of artificial potential field.

the static environment. It belongs to the information representation method of the neuron input, and there is the uncertainty of learning errors. The advantage is that the requirements for prior knowledge are not too high or not required, and the ability to adapt is very strong. The disadvantage is the large amount of calculation, and it is difficult to establish effective learning rules

- (5) The fuzzy logic theory algorithm is suitable for advanced data fusion in a static operating environment [26], and it is a propositional information expression method with member uncertainty. The advantage is that it can clearly describe the problem, is close to human language habits, and has good scalability. The disadvantage is that the amount of calculation is large

2.7. Path Planning Based on Artificial Potential Field. The basic idea of the artificial potential field is to construct the gravitational potential field of the target point and the repulsive potential field of the obstacle after determining the position of the target point and the obstacle and determining the direction of falling by determining the target position. By finding the descending direction of the combined potential field function of the two possible fields, the best path without collision is determined. The schematic diagram of the artificial potential field is shown in Figure 3:

When the robot moves to the target point, the repulsive force field function generated by the obstacle on the robot is U , and the generated potential energy is related to the distance (d) between the obstacle and the robot. The specific relationship is shown in the repulsive force field function. The form of the field function is

$$U_{\text{rep}}(X) = \begin{cases} \frac{K_r}{d}, & d < d_m, \\ 0, & d > d_m. \end{cases} \quad (1)$$

Among them, K_r represents the repulsive force field constant, X represents the position of the robot, Y represents the position of the obstacle, and d_m is the range of influence of the repulsive force field.

The repulsion of obstacles to the robot is generated by the virtual repulsion potential field, and the direction is the negative gradient direction of the repulsion potential field, and its expression is

$$F_{\text{rep}}(X) = -\nabla U_{\text{rep}}(X). \quad (2)$$

When d tends to 0, F tends to infinity, indicating that the robot collides with an obstacle. In order to prevent this from happening, generally set a safety distance threshold d_0 ; when d tends to d_0 , F tends to infinity, and the robot's repulsive force expression is

$$F_{\text{rep}}(X) = \begin{cases} K_r \times \left(\frac{1}{(d-d_0)^2} - \frac{1}{(d_m-d_0)^2} \right), & d \leq d_m, \\ 0, & d > d_m. \end{cases} \quad (3)$$

Gravitation is the attraction of the target point to the robot. As the robot approaches the target, the force will gradually decrease. When the robot is too close to the target, the force tends to zero, which can be ignored. In this article, the gravity field function is considered as

$$U_{\text{rep}}(X) = \frac{1}{2} K_a \cdot d^2. \quad (4)$$

Among them, K_a is the gravitational potential field constant, and the response gravitation generated by the gravitational field is

$$F_{\text{att}}(X) = -\nabla U_{\text{att}}(X). \quad (5)$$

Resynthesize (1) which is the expression of the gravitation on the robot:

$$F_{\text{att}}(X) = K_a \cdot d. \quad (6)$$

The direction of gravity is from the robot to the target point.

The resultant potential field of the robot's running space is the combination of the gravitational field and the repulsive field experienced by the robot. According to the superposition principle of the potential field, the expression of the whole situation field is obtained as

$$U(X) = U_{\text{att}}(X) + U_{\text{rep}}(X). \quad (7)$$

The resultant force experienced by the robot is shown in

$$F(X) = -\nabla U(X) = -\nabla U_{\text{att}}(X) - \nabla U_{\text{rep}}(X) = F_{\text{att}}(X) + F_{\text{rep}}(X). \quad (8)$$

2.8. Realization of Ant Colony Optimization Algorithm and Path Planning. There are two core problems in the ant colony optimization algorithm, ant coding and fitness function construction. For coding, the distance between the planning origin point and the planning target point is divided into $D + 1$ equal parts along the X axis, and the ordinate value is the ant code. Assume that the total number of ants is n . The process ant colony optimization algorithm is described in path planning:

Objective function:

$$f(x, y) = \min f(x, y). \quad (9)$$

This is the path length. When moving, $\text{ant}_k^k (1, 2, \dots, n)$ determines the next transmission direction based on the amount of information. At time t , the corresponding probability of the ant from position i to position j is shown in

$$p_{ij}^k = \begin{cases} \frac{\tau_{ij}^\alpha(t) \cdot \eta_{ij}^\beta(t)}{\sum_{r \in S_i^k} \tau_{ir}^\alpha(t) \cdot \eta_{ir}^\beta(t)}, & j \in S_i^k, \\ 0, & j \notin S_i^k. \end{cases} \quad (10)$$

Among them, $\eta_{ij}(t)$ is a local heuristic function, the parameters α and β are used to modify the $\tau_{ij}(t)$ and $\eta_{ij}(t)$ for the weight of the entire mobile probability effect, and S_i^k is the feasible region of position i at time K , and the feasible region is updated in the iterative process.

$$\Delta\tau_{ji}(t) = \frac{1}{f(x_i, y_i)}. \quad (11)$$

It is the relative path length.

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t). \quad (12)$$

ρ is the coefficient of pheromone volatilization, which is 0.8 in this article. Over time, the update formula is

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \sum_{k=1}^n \tau_{ij}^k. \quad (13)$$

Among them, $\Delta\tau_{ij}^k$ is the amount of information left by k ant; if the ant passes (i, j) in the k -th cycle, then

$$k\Delta\tau_{ij}^k = \frac{\tau_{ij}^0}{L_k}. \quad (14)$$

L_k is the total length of all paths in the k -th cycle, or $\Delta\tau_{ij}^k = 0$.

3. Experiments on Software Design and Research of Intelligent Sensor Robot System Based on Multidata Fusion

3.1. Examples of Multisensor Fusion Robots. At present, intelligent mobile robots basically have visual sensors, tactile sensors, ultrasonic sensors, and infrared sensors through fusion methods. One of the key technologies is to improve the ability of mobile robots to avoid obstacles under sensor data. Some examples of multisensor fusion for mobile robots are shown in Table 1.

3.2. Obstacle Avoidance Experiment

3.2.1. Static Obstacle Avoidance Experiment of Dynamic Window Method. The static obstacle avoidance experiment of the mobile chassis is completed based on the dynamic window method. The mobile chassis will drive forward and will change the driving direction when encountering obstacles, thus avoiding static obstacles and reaching the designated position. During the test, the average running speed of the mobile chassis was 0.29 m/s, and the average time was 30 s. The static obstacle avoidance physical map of the dynamic window method is shown in Figure 4 (the process is from left to right):

3.2.2. Dynamic Window Method Dynamic Obstacle Avoidance Experiment. When the dynamic windowing method is used for local route planning, it is impossible to predict the trajectory of the moving object and replan the route, and it is difficult to deal with dynamic obstacles. When the dynamic target completely blocks the path of the moving chassis, the moving chassis will detect the obstacle, replan the path, and then move backward to avoid encountering obstacles when turning. It can be concluded that the dynamic window method has limitations for the obstacle avoidance of dynamic targets. During the test, the average running speed of the mobile chassis was 0.23 m/s, and the average time was 35 s. The dynamic obstacle

TABLE 1: Multisensor fusion robot example.

Robot	Sensor type	Fusion technology
HILARE	Sound, vision, laser ranging	Weighted average
DARPA	Vision, sonar, laser ranging	Small range average increase
Stanford	Semiconductor laser, tactile, ultrasonic	Kalman filtering
RANGER	Semiconductor laser, tactile, ultrasonic	Jacobian tensor and Kalman filtering
LIAS	Ultrasonic, infrared	Multiple fusion
Alfred	Sonar, sound, color camera	Logical reasoning
ANFM	Camera, infrared, ultrasonic, GPS	Neural networks

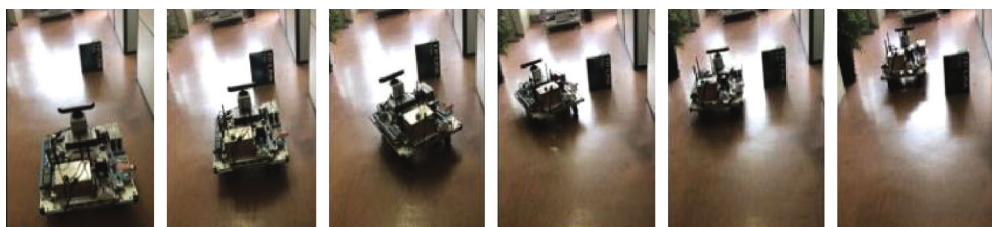


FIGURE 4: The physical image of static obstacle avoidance based on dynamic window method. (This picture begins with “Research on Mobile Robot System Design and Map Navigation Based on Multisensor Fusion.”)

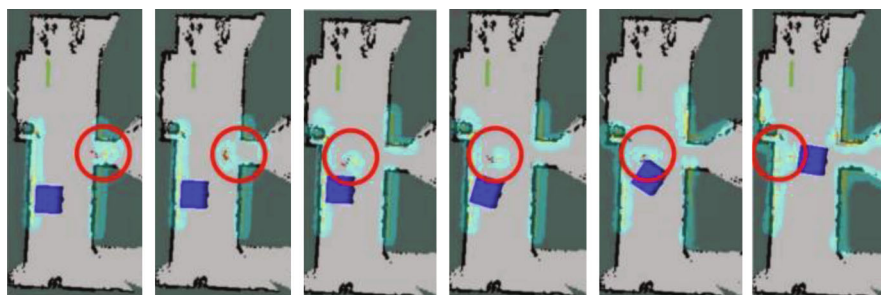


FIGURE 5: Dynamic obstacle avoidance based on dynamic window method. (This picture begins with “Research on Mobile Robot System Design and Map Navigation Based on Multisensor Fusion.”)

avoidance diagram based on the dynamic window method is shown in Figure 5 (the process is from left to right).

3.2.3. Dynamic Obstacle Avoidance Experiment Based on Artificial Potential Field Method. In the human-in-field method, the extracted dynamic obstacle model is used to add the speed term of the obstacle to the method, and the dynamic obstacle avoidance experiment is carried out. The experimental conditions are basically the same as the dynamic window method. The mobile chassis predicts the trajectory of the pedestrian based on the speed of the pedestrian and determines in advance whether a collision will occur, and the local path planning will change the trajectory of the robot in real time to achieve the goal of dynamic obstacle avoidance. During the test, the average running speed of the mobile chassis was 0.23 m/s, and the average time was 29 s. The physical map of dynamic obstacle avoidance based on the improved artificial potential field method is shown in Figure 6 (the process is from left to right).

See Table 2 for the analysis and comparison of the above three groups of mobile chassis obstacle avoidance experiments. It can be seen from the table that the dynamic window method has a good effect when applied to static obstacle avoidance and can meet the requirements of normal use, but it is not well applied in dynamic obstacle avoidance, the path planning efficiency is low, and there is a risk of collision. The artificial potential field method can successfully predict the trajectory according to the moving speed of the obstacle and plan the possible collision path in advance. Compared with the dynamic window method, it greatly improves the success rate and efficiency of obstacle avoidance.

4. Software Design Research of Intelligent Sensor Robot System Based on Multidata Fusion

4.1. Intelligent Robot Obstacle Avoidance System. Sensors are the main tool that connects the robot with the external

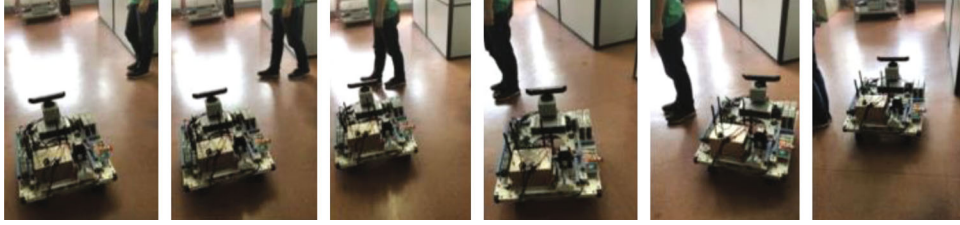


FIGURE 6: Dynamic obstacle avoidance based on improved artificial potential field method. (This picture begins with “Research on Mobile Robot System Design and Map Navigation Based on Multisensor Fusion.”)

TABLE 2: Obstacle avoidance experiment comparison.

Experimental scene	Local path planning method	Success rate	Moving chassis speed	Average running time
Static obstacle avoidance	Dynamic window method	80%	0.29 m/s	30 s
Dynamic obstacle avoidance	Dynamic window method	40%	0.23 m/s	35 s
Dynamic obstacle avoidance	Improved artificial potential field method	90%	0.23 m/s	29 s

TABLE 3: Ultrasonic sensor test data.

Actual distance (m)	0.3	0.4	0.6	0.7	0.9	1.4	1.9	2.0
Test distance (m)	0	0.389	0.588	0.679	0.888	1.378	1.898	1.967
Actual distance (m)	2.4	2.8	3.3	4.0	4.6	5.0	5.5	6.0
Test distance (m)	2.365	2.766	3.279	3.999	3.554	4.964	5.454	6.098

environment, and the choice of sensors is the most important for realizing the autonomous movement of intelligent robots. The intelligent robot platform is equipped with 4 ultrasonic sensors and 2 infrared sensors, both of which can realize the ranging function. The ultrasonic sensor has a wide range and cannot detect obstacles at close range. Infrared sensors can make up for the shortcomings of ultrasonic sensors that cannot be detected at close range. Therefore, in this chapter, we mainly study how to use ultrasonic and infrared sensors to avoid obstacles.

4.1.1. Ultrasonic Sensor. Ultrasonic sensors are widely used as noncontact distance measurement sensors. The working principle is that the ultrasonic transmitter emits a pulse signal of a specific frequency in a specific direction. When an obstacle is encountered, the pulse signal is reflected and received by the receiving end. The reflected signal can calculate the distance from the transmitting end to the obstacle by measuring the time difference from transmission to reception and the propagation speed of ultrasonic waves in the medium. Since the working environment of the robot is indoors, the sound wave propagates in the medium at a speed of 340 m/s under the condition that the accuracy of the distance measurement is not high. The distance measurement experiment is performed on a single ultrasonic sensor at room temperature. The experimental test results are shown in Table 3.

The above results are all tested in an ideal experimental environment. The difference between the actual distance and the test distance is very small. When the robot is in

TABLE 4: Infrared sensor characteristics.

GP2Y0A02YK0F parameters	
Distance measurement range	20-140 cm
Output type	Analog voltage
Package dimensions	28.5 × 12 × 12.5 mm
Current consumption	22 MA
Voltage	4~5 V

motion or the environment is not ideal, the measurement results have greater uncertainty.

4.1.2. Infrared Sensor. The infrared sensor system is a measurement system that uses infrared as the medium. It has the advantages of simple operation, fast measurement speed, and high accuracy. It is widely used in various fields of daily life, especially in the field of robotics, as a distance sensor. In order to reduce the cost of the experiment and improve the accuracy of the system, we carried out the infrared sensor circuit design, carried out the ranging experiment at the same time, and calculated the accuracy of the infrared sensor, laying the foundation for multisensor data fusion.

When the infrared sensor emitted by the infrared sensor encounters an obstacle, it will be reflected to the sensor's receiving head. During this process, the counter will detect the number of clock pulses passed to obtain the distance between the robot and the front of the obstacle. The sensor selected in this article must provide a voltage output proportional to the measured distance. The infrared sensor is a

TABLE 5: Infrared sensor ranging experiment data.

Actual distance (m)	0.3	0.4	0.6	0.7	0.9	1.4	1.9	2.0
Test distance (m)	0	0.419	0.688	0.699	0.918	1.398	1.888	1.997
Actual distance (m)	2.4	2.8	3.3	4.0	4.6	5.0	5.5	6.0
Test distance (m)	2.335	2.774	3.265	3.976	3.577	4.988	5.464	6.045

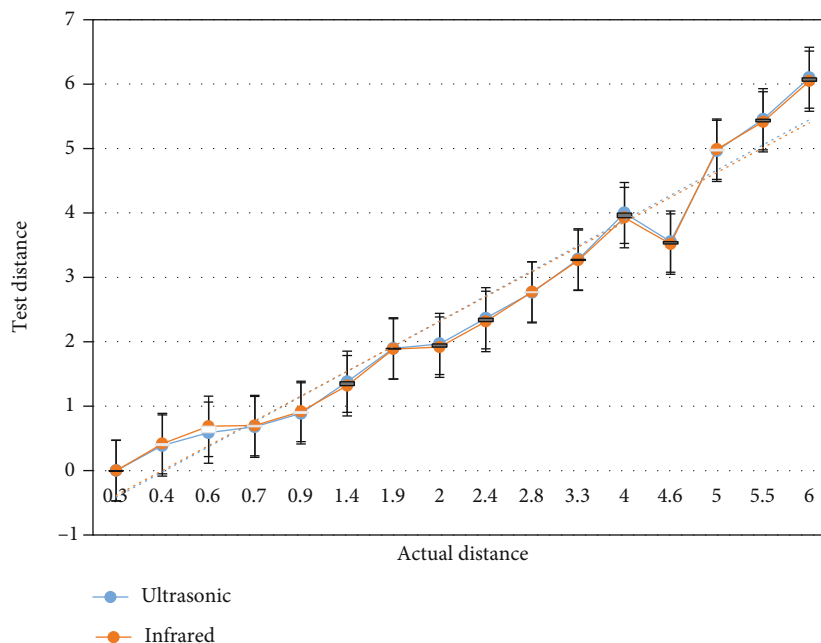


FIGURE 7: Comparison of actual distance and test distance between ultrasonic sensor and infrared sensor.

Sharp GP2Y0A02YK0F analog distance sensor. The main characteristics of the infrared sensor are shown in Table 4.

Since the working environment of the robot is indoors, the sound wave propagation speed in the medium is 340 m/s under the condition that the accuracy of the distance measurement is not high. The distance measurement experiment is carried out on a single infrared sensor at room temperature. The experimental test results are shown in Table 5.

4.2. Ultrasonic Sensors and Infrared Sensors. Through the above experimental analysis, it can be concluded that whether it is an ultrasonic sensor or an infrared sensor, the error between their test distance and the actual distance is very small. From Tables 3 and 5, we can get that the minimum error between the test distance and the actual distance is 0.001. The comparison between the actual distance and the test distance between the ultrasonic sensor and the infrared sensor is shown in Figure 7.

5. Conclusion

This paper studies the software design of an intelligent sensor robot system based on multidata fusion, preprocessing the environmental information data collected from each sensor of the robot, processing and fusing the data collected from each sensor, and planning the movement path of the robot.

Simulating and preprocessing data collected from sensors using ant colony optimization algorithms can significantly improve the accuracy and effectiveness of the data. The ant colony algorithm can perform fusion and path planning and speed up fusion based on ensuring accuracy. Finally, in the obstacle avoidance experiment of intelligent robots, we can conclude that multisensor data fusion technology is very necessary for intelligent robots, because we can make intelligent robots avoid obstacles through ultrasonic sensors and infrared sensors.

Data Availability

No data were used to support this study.

Conflicts of Interest

There are no potential competing interests in our paper.

Authors' Contributions

All authors have seen the manuscript and approved to submit it to this journal.

Acknowledgments

This work was supported by the Institutional Foundation of the First Affiliated Hospital of Xi'an Jiaotong University (No_2018RKX-08).

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