Research Article

Intelligent Obstacle Avoidance Algorithm for Mobile Robots in Uncertain Environment

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The application of mobile robots and artificial intelligence technology has shown great application prospects in many fields. The ability of intelligent obstacle avoidance is the basis for the deep application of mobile robots. However, there are often more or less uncertain factors in the actual operating environment of the robot, such as people or objects that are not updated in time or temporarily appear. Therefore, it is an important step to complete the automatic learning of obstacle avoidance for mobile robots. In a nondeterministic environment, a mobile robot intelligent obstacle avoidance algorithm based on an improved fuzzy neural network with self-learning is firstly proposed. The mobile robot intelligent obstacle avoidance system is constructed through the reaction layer, the deliberation layer, and the supervision layer. Through the analysis of sensor performance, model accuracy, path obstacle avoidance optimization, and obstacle avoidance simulation, the following conclusions are drawn. First, through network training, the accuracy rate of the test set is stable at 98%, and the loss of the function value has also been reduced from the original 0.79 to 0.08, which is 10 times smaller. Second, the traditional single sensor cannot meet the obstacle avoidance requirements of robots, and mobile robots must combine multipurpose technology. Third, the algorithm in this paper encounters the following. When there are obstacles, the path is dominated by straight lines, obstacle avoidance planning is optimal, and the distance is shorter. Fourth, the larger $N:M$, the larger the solution space, indicating that this algorithm gradually improves the search efficiency to the greatest extent and can handle any form of medium and large scale task allocation problem.

1. Introduction

Robot technology is an important manifestation and symbol of the degree of industrial automation and the national high-tech level. Robot technology is a high-tech formed on the basis of interdisciplinarity. It is one of the hot spots of current scientific research [1]. Mobile robots are widely used in various fields, especially in harsh and dangerous environments such as military reconnaissance, antinuclear pollution, mine clearance, and material handling in civil use. Therefore, mobile robots greatly facilitate people’s production and life. The research on robots has received widespread attention.

On the basis of the continuous improvement of artificial intelligence, the development of robot technology is becoming more and more intelligent, and the ability of mobile robots to intelligently avoid obstacles is an important indicator of their intelligence [2]. They not only reflect the efficiency, feasibility and energy consumption of mobile robot motion but also reflect the way the robot detects obstacles, processes obstacle information, and avoids obstacles. Today’s mobile robots have moved from structured work spaces to uncertain environments [3]. In an unknown and uncertain environment, it is an important step for mobile robots to learn to avoid obstacles autonomously. It enables mobile robots to have human-like behaviour.
strategies and avoid obstacles, thereby realizing intelligent navigation of mobile robots [4]. How to intelligently avoid these obstacles unknown to the environment map in an uncertain environment is a key link of mobile robots and one of the research hot spots of robotics.

At present, great progress has been made in the research of autonomous obstacle avoidance algorithms for mobile robots in the world, and many algorithms are applied in the autonomous obstacle avoidance systems of mobile robots. These intelligent obstacle avoidance algorithms mainly include fuzzy control, grid map, artificial potential field, and neural network [5]. The fuzzy control algorithm has the advantages of simple algorithm, easy to understand, and strong robustness, but there are also problems such as the need for experience in design, low control accuracy, and no learning ability; neural network algorithms can use a large amount of data to train models, which can automatically learn parameters to obtain the final end-to-end network model, but there are problems of high network complexity and practicability. This paper fully considers the practicability and operability of intelligent obstacle avoidance of mobile robots, combines fuzzy control algorithm with neural network algorithm, and takes the lead in proposing an intelligent obstacle avoidance algorithm for mobile robots based on improved fuzzy neural network with self-learning.

2. Related Work

A mobile robot is a robot system that completes certain work functions. It can sense the external environment and its own situation through sensors and realize its autonomous movement in an environment with obstacles [6]. Mobile robots have become a research hot spot in robotics because they have shown more and more extensive application prospects in various aspects of agriculture, industry, aerospace, medicine, and human life [7].

The earliest research on mobile robots was from 1966 to 1972, when Nils Nilssen and Charles Rosen of Stanford Research Institute developed an autonomous mobile robot [8]. In the 1980s, a number of universities such as Stanford and MIT established a special scientific research team for ALV research [9]. In the 1990s, Japan developed working robots that can operate in extreme environments and successfully developed humanoid robots [10]. In 2003, Tsinghua University in China independently developed the robot automatic navigation system [11]. All over the world, Japan has always been at the forefront of the world in the field of humanoid robots and wheeled robots. The ASIMO biped walking robot developed by Honda represents the highest level in the world. ASIMO uses a variety of sensors in the realization of its functions, including cameras on the head, ultrasonic sensors around, and ground pressure sensors on the bottom of the feet. In terms of functional realization, ASIMO not only realizes the functions of walking, positioning, and navigation but also adds functions such as face recognition and communication by voice or gesture [12].

In recent years, breakthroughs have been made in the research on the theory and algorithm of navigation control of mobile robots in unknown environments. Yan Z. pointed out that based on global path planning, navigation and obstacle avoidance are performed according to the planned path method [13]. Jin J. combined fuzzy logic and grid graph in the target navigation of mobile robots, using the minimum risk criterion as the evaluation function to improve the effect of path planning [14]. Zafar M. proposed a learning algorithm based on neural network error backpropagation to adjust the membership function parameters of the fuzzy logic system to improve the trajectory smoothness of the mobile robot [15]. Cui Min applied the improved neural network algorithm to the path planning of mobile robots, which improved the operation efficiency of the algorithm [16]. Chen D. proposed a reinforcement learning mechanism based on fuzzy neural network, which utilizes the residual in the learning algorithm and obtains a better algorithm convergence speed in the navigation process of the mobile robot [17].

In the previously mentioned research, different algorithms are used in mobile robot path planning and navigation and obstacle avoidance, and the performance of the system has been improved to a certain extent. However, in the nondeterministic environment, the previously mentioned obstacle avoidance and planning algorithms have some deficiencies in flexibility, real-time, humanization, and intelligent performance. This paper focuses on the problems existing in the previously mentioned algorithms. In a nondeterministic environment, an intelligent obstacle avoidance algorithm for mobile robots based on improved fuzzy neural network with self-learning is firstly proposed, which improves the flexibility, autonomy, and stability of mobile robots.

3. Implementation of Intelligent Obstacle Avoidance Algorithm

This paper fully considers the importance of obstacle avoidance for mobile robots in nondeterministic environments and proposes an intelligent obstacle avoidance algorithm for mobile robots based on improved fuzzy neural network autonomous learning. First, in view of the high complexity and poor real-time performance of the fuzzy algorithm, the necessary simplification of the fuzzy neural network is carried out to perform image preprocessing and rough positioning of obstacles. Second, the parameters of the fuzzy membership function are automatically and dynamically adjusted by the neural network with self-learning ability, so that the fuzzy control rules have stronger object adaptability. Furthermore, for dynamic obstacles in autonomous obstacle avoidance, edges are introduced. The detection operator implements the dynamic obstacle avoidance strategy of the mobile robot.

3.1. Improved Fuzzy Neural Network Algorithm. This paper applies the improved fuzzy neural network algorithm to the field of image processing, analyzes the image to detect obstacles by counting the neurons in the visible range, and uses the knowledge of distance images to convert the detection results to finally determine the location of the obstacles.
3.1.1. Image Preprocessing and Coarse Positioning of Obstacles. Image preprocessing includes image greyscale, image denoising, and effective image region selection. Image greyscale is to complete the conversion from colour to greyscale. In the system, the video image format conversion is completed through the acquisition of the camera. The value of the three colour components of R, G, and B in the RGB space of the image is stored in the image, and greyscale can be achieved by using
\[
grey = 0.5 \times Red + 0.23 \times Green + 0.27 \times Blue. \tag{1}\]

The size of the redundancy is related to the probability of occurrence of each basic element in the information. Its expression is as follows:
\[
M(X) = E[\log q(ai) \times 10] = \sum_{i=0}^{n} q_i(ai) \log q_i(ai). \tag{2}\]

Among them, ai is the event in the sample population X. The previously mentioned formula indicates that the more average the number of occurrences of each sample event, the greater the number of different events in the sample population X, and the greater the amount of information. If there are N groups of samples, X1, X2,..Xn, the corresponding sample numbers are \(k_1, k_2,..k_n\) and the information entropy is \(M_1, M_2,..M_n\). The unit information entropy is the average value of the information contained in the unit sample in the sample population, which is embodied as the ratio of the population neuron to the number of spatial samples, namely,
\[
D(X) = M(X) \times n = \sum_{i=0}^{n} q_i(ai) \log q_i(ai) \times \frac{1}{n}. \tag{3}\]

Among them, qi represents the probability of the occurrence of a pixel whose gray level is i; k is the number of gray levels whose qi is not zero in all gray levels. In the actual experiment, the horizontal image analysis process is as follows: select a row of pixels as the data source for statistics qi; that is, count the gray level distribution of the pixels in each row, and obtain the corresponding pixel points in each gray level i. The number of pixels, qi, is the ratio of the number of pixels contained in the gray level to the total number of pixels in the row; then, the unit information entropy is calculated for all gray levels whose qi is not 0.

3.1.2. Accurate Positioning of Obstacles in the Image. Since the experimental environment is relatively simple, the relatively simple Roberts edge detection operator can be used for detection to obtain edge point information, which can effectively improve the real-time performance of the system. The Roberts operator in an image pixel array looks like this
\[
k(a, b) = \sqrt{[t(a, b) + t(a + 1, b + 1)]^2 - [t(a, b + 1) + t(a + 1, b)]^2}. \tag{5}\]

The Roberts operator is a diagonal derivative computed in a 2x2 neighbourhood. In practical applications, the previously mentioned formula can be replaced by a simplified calculation form, which is expressed as follows; that is, the absolute value of Roberts is replaced.
\[
k(a, b) = |t(a, b) + t(a + 1, b + 1)| + |t(a, b + 1) + t(a + 1, b)|. \tag{6}\]

3.1.3. Distance Image Obstacle Location. The range image stores the depth information of the ray associated with each pixel and the first focus of the scene observed by the camera. According to the idea of interpolation, using the geometric principle of camera imaging, using Manlius's theorem, establish a three-dimensional distance function, calculate the distance from any position in the monitoring area to the camera, and establish a distance image about the distance between any point in the monitoring area and the camera:

\[
a = \arctan h \times y1, \tag{7}\n\beta = \arctan h \times (y1 - y2), \tag{8}\n\lambda = \arctan(x1 \times y1), \tag{9}\n\]

where \(h, y1, y2,\) and \(x1\) are data that can be measured. After obtaining \(a, \beta,\) and \(y1, x2, y2,\) and \(x2\) can be obtained from the trigonometric function relationship, and the derivation formula is as follows:
\[
y = h \times \tan[(45 + a) - (s_j - u)s_y \times (a + \beta)], \tag{10}\nx = y \times \tan[s_x + v] \times s_x + y, \tag{11}\nB = \sqrt{x^2 - y^2} \times \sqrt{x^2 + y^2}. \tag{12}\n\]

Among them, B is the distance between the vertical projection points of the camera coordinates; \(S_x\) and \(S_y\) are the total number of pixels in the x and y directions in the image.
plane; $u$ and $v$ represent the horizontal and vertical imaging planes, respectively.

The position of the target point in ABCD can be obtained by formulas (7)–(9), that is, the coordinates of the target point in the world coordinate system. By analyzing the image through image neurons and edge information in the image, the characteristic edge points of obstacles can be obtained. Through the knowledge in this section, these correspondences with the world coordinate system are established to obtain the position of the obstacle in the actual situation.

3.2. Intelligent Obstacle Avoidance System. A very important task area for mobile robots is navigation, which is to find a route so that it can move safely without collisions around all obstacles. This planning technology that can autonomously avoid obstacles and complete tasks is the frontier technology for intelligent mobile robots to achieve autonomous behaviour control. Therefore, it is the most basic problem to apply the improved fuzzy neural network algorithm to the intelligent obstacle avoidance system of mobile robots. The mobile robot intelligent obstacle avoidance system designed in this paper integrates different functions in the system, as shown in Figure 1.

Much of the structure of the intelligent obstacle avoidance system involves planning, using a reactive planner called PRS-L. PRS-L can accept human natural language instructions, and then, start to run navigation tasks and perceptual recognition routines [18]. Both planning and execution rely on a locally aware spatial-centrist model of the environment. The reactive components of an intelligent architecture consist of behavior. These behavior extract virtual sensor input and output fuzzy rules from the local perception space of the central environment model and then synthesize control instructions through fuzzy logic.

From the intelligent obstacle avoidance system, it can be seen that a hybrid architecture should have the following modules and objects.

Sequencer agent is used to generate the set of tasks required to complete the subtasks and to determine all timing and activation conditions. Timing is usually represented as a correlation network or finite state machine, and sequencers can generate these structures and modify them dynamically [19].

Resource manager is used to allocate resources for behavior including selection of schema libraries.

Cartographer is used to generate, store, and maintain map or spatial information and provide a means of accessing data.

Mission planner interacts with the user, passes instructions to the robot, and generates mission plans.

Performance supervision and problem solving agents are used to let the robot notice if it is making progress.

3.3. Intelligent System Hierarchy. Because the mobile robot obstacle avoidance system adopts the modular design method based on multi-agent, the functions are independent of each other. Therefore, it is very easy to realize the function expansion and can be used as the design and experiment platform of the ideal hybrid architecture. In this chapter, we are based on the mobile robot intelligent obstacle avoidance architecture, follow the general design principles of intelligent system structure, and add supervision management and learning functions on the basis of the original hybrid structure. Through the improved fuzzy neural network algorithm, the robot can learn behavior autonomously in the dynamic unknown environment so as to adapt to the changes of the environment, as shown in Figure 2.

Reactive behaviour control layer contains reflective behaviour and reactive behaviour, as well as a structure for coordinating reactive behaviour. Reflective behaviour is used to react to emergencies in the environment, or it can be a single control rule. For the navigation tasks of mobile robots, reactive behaviors are designed for obstacle avoidance, goal orientation, and roaming. These behaviors can be pare-designed by expert experience or acquired through learning and evolution. All behavior can directly respond to the information felt from the outside world and can also receive control signals from the deliberation layer and the supervision layer to perform actions.

Regarding the deliberate behaviour control layer, the task for the navigation class includes five basic modules, and other functions can be added on this basis. The modules are environment model knowledge base, task planning module, positioning module, navigation module, and sequencer. The environmental model knowledge base can directly receive the environmental model transmitted from the outside world and store it in the knowledge base through human-computer interaction and can also generate a map based on the collected sensor information, maintain the map information in time, and provide orientation data to other modules. The task planning module receives the instructions input by the user and transmits it to the robot for task planning. The positioning module uses the shaft angle encoder combined with the feature quantity extracted from the external sensor data to determine the position of the robot in the environment at each moment. Navigation accepts the task from the task planning module and calculates the path and decomposes it into subtasks. The sequencer is used to generate the task set required to complete the subtasks and determine all the timing and activation conditions. When the purposeful planning is required, the reaction layer obtains the ordered actions through the sequencer.

Supervise and manage the behaviour control layer: used to monitor the execution of the deliberation layer and the behaviour layer, so that the robot can notice whether it is making progress. At present, five modules are set up, namely, a cross module for coordinating and reflecting deliberation behavior, a fault supervision module, a supervision module for the execution of behavior at the reaction layer, a supervision module for behaviour planning at the deliberation layer, and a learning evolution unit. The learning evolution unit has two functions. One is to learn the local optimal path planning behaviour in a static environment of deliberation behaviour, and obtain the design of reactive behaviour autonomously. The second is to use the collected sample data for training and learning in a dynamic
environment to establish a prediction model for dynamic obstacle avoidance. Learning the functions of evolution could enable robots to autonomously adapt to environmental changes and enhance their intelligence.

3.4. Obstacle Avoidance Control Process. In robot route planning, various information obtained from the robot itself and its environment is synthesized, enabling the robot to understand its environment and make decisions through
controller processing. So as to avoid obstacles, find the optimal path and move autonomously [20]. Figure 3 shows the flowchart of the mobile robot path planning.

The mobile robot is equipped with a positioning system that can detect the global position and heading of the mobile robot. Six ultrasonic sensors are used to detect local obstacle information. The mobile robot performs detection every 1s, and the acquired sensor data is fused as the input of the controller. By verifying the effectiveness of the previously mentioned improved fuzzy neural network algorithm, a system simulation model is established in Mat lab with the fuzzy logic toolbox software to simulate the neural network algorithm. In this simulation system, the steps of path planning simulation are as follows.

1. Establish environmental information: environmental information is to establish the coordinates, dimensions of obstacles, and the starting point and target point of the robot.
2. Establish a simulated robot, including some parameters such as robot size and moving speed. According to the kinematic model of the robot in the actual system, it is assumed that the travelling speed of the mobile robot is 0.6 m/s, and it can realize 360° in situ.
3. Establish a simulated sensor: used to perceive the simulated environment information, that is, to obtain the value of the obstacle distance information \(d\) and the target direction angle \(\theta\).
4. The robot controller is designed by an improved fuzzy neural network algorithm, and the driving instructions of the robot are obtained by analyzing the obstacle and target data obtained by the sensor.
5. Transmission of control instructions: the driving instructions are transmitted to the simulated robot, the mobile robot moves according to the instructions, and then the map coordinates of the robot after executing the driving instructions are calculated; repeat steps (3) to (5) until the robot reaches the predetermined target point.

4. Intelligent Obstacle Avoidance Algorithm

4.1. Algorithm Accuracy Analysis. In this experiment, the two network models before and after the improvement were used for training, respectively, and the training results were compared after 300 times of effective training. Before training, you need to import the saved network model data in advance, and use the training data set to continue training the network model before the improvement. At the same time, the loss value and the accuracy curve are obtained, and the accuracy curve of the test set is obtained, as shown in Figure 4.

It can be seen from Figure 4 that since the training, the loss value has been continuously reduced and the accuracy has been continuously improved in the process of reverse gradient learning. This is a supervised learning process. Before adding the \(1 \times 1\) constitutional layer, after multiple training, the final test set accuracy rate was stable at about 95%. After adding the \(1 \times 1\) constitutional layer, the network is retrained, the test set accuracy rate is stable at 98%, and the loss function value is also reduced from the original 0.79 to the current 0.08, which is 10 times smaller. Since the added \(1 \times 1\) constitutional layer contains nonlinear units, the nonlinear expression ability of the model is improved. After adding \(1 \times 1\) to two different curves, the fluctuation is obviously reduced compared with the previous curve, and it is relatively stable.

4.2. Sensor Property Index Analysis. The sensor control system and the information processing system constitute the robot’s obstacle avoidance system. Among them, the sensor control system is composed of sensors and microprocessors that obtain environmental information. It mainly collects information from unknown environments, which is the only way for robots to understand environmental information. Therefore, the reasonable configuration of the sensor determines the accuracy of the system’s acquisition of the external environment.

As can be seen from Figure 5, the radar has the best performance index and high cost. Ultrasonic and infrared have the lowest cost. In view of the need for obstacle avoidance, combined with the cost of the sensor, the performance index of the collected information, the hardware implementation circuit, volume, and other comprehensive factors, the sensor control system in this paper mainly uses ultrasonic and infrared sensors to collect the obstacle distance of the external environment and electronic compass to obtain the target object. Considering the unknowns and complexity of the external environment, the multipurpose technology is applied to the mobile robot obstacle avoidance system, and the hardware and algorithms are processed accordingly to enhance the intelligence of the robot.

4.3. Path Obstacle Avoidance Optimization Analysis. In a complex environment with obstacles, the ultimate goal of path planning is to solve an optimal route, so that the robot can move smoothly and avoid all obstacles without collision [21]. In practical applications, the environment is unknown to the mobile robot. The unknown environment, the detection accuracy of the obstacle detector and the difference of the path planning algorithm have a great influence on whether the path planning can be successfully implemented. This paper compares and analyzes the experimental paths of the BUG algorithm and the improved fuzzy neural network algorithm.

It can be seen from Figure 6 that when the BUG algorithm is used, the robot moves along the edge contour of the obstacle. When it can move to the target point, it will directly leave the edge of the obstacle and move beyond the target point. It is not limited to the distance judgment between the obstacle and the target point. H1 and H2 are the arrival points, and L1 and L2 are the separation points. When using
the intelligent algorithm, the robot initially moves along the line connecting the starting point and the target point. When encountering an obstacle, it moves along the tangential direction of the obstacle until no obstacle is detected and then updates the current point to the target point. It extends the updated main line and repeats this process until the target point is reached. After comparison, it is found that the improved fuzzy neural network algorithm in this paper, the path distance is dominated by straight lines, the distance is shorter, and the distance is shortened by 5–10m.

4.4. Obstacle Avoidance Algorithm Simulation. In order to verify the performance of the algorithm, a lot of simulation research has been done in this paper. Let the values of \( N \) and \( M \) be 4, 10, 30, and 60, respectively, the selection probability is 0.1, the cross-mutation probability is 0.08, the \( a \) and \( \beta \) values are both 1, and the population evolution stops at 200
or 1000 generations. Research the convergence performance of the algorithm evolution under the same parameters: the evolution algebra when the algorithm converges and the execution time is consumed by the evolution calculation. The changes of the maximum fitness value during the evolution of each group of experiments are shown in Figure 7.

It can be seen from the figure that, with the increase of \( N:M \), the method will gradually improve the search efficiency. The larger \( N:M \) is, the larger the solution space is, but the convergence speed does not change, which shows that the search efficiency of this method is the largest as the value increases. When the solution space of the problem is large, the speed of convergence is obviously slowed down, the algebra of convergence is improved, and the convergence time is prolonged. This further verifies that the method is suitable for medium and large scale problem spaces. In summary, the algorithm can handle any form of medium-to-large-scale task assignment problem.

5. Conclusion

The ability to autonomously avoid obstacles is the main indicator to measure the intelligence of mobile robots, and it is also an important condition for intelligent robots to drive safely [22]. This paper is the first to propose an intelligent obstacle avoidance algorithm for mobile robots based on improved fuzzy neural network, which achieves precise positioning through adaptive learning. Following the general principles of intelligent control system design, on the basis of response and deliberation, a monitoring layer is added. Supervise and coordinate the implementation of deliberative layer behaviors to learn adaptive behaviors in unknown environments. By collecting sample data for training, it learns to build predictive models to avoid dynamic obstacles. Through the obstacle avoidance experiment simulation, the accuracy and real-time performance of the system are further verified, and finally, a good obstacle avoidance effect is achieved.
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 that there are no conflicts of interest or ethics in this article.

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