Received: 1 November 2021 | Revised: 22 February 2022 | Accepted: 24 February 2022 | Published online: 21 March 2022

RESEARCH ARTICLE

Journal of Computational and Cognitive Engineering
2022, Vol. 1(4) 201–208
DOI: 10.47852/bonviewJCCE597820205514

BON VIEW PUBLISHING

Research on Robot Path Perception and Optimization Technology Based on Whale Optimization Algorithm

Jie Zan[1,*]

[1] *College of Mechanical and Electrical Engineering, Xi'an Polytechnic University, China*

Abstract: With the development of modern sensor technology, the automatic movement of robot has become a reality, and improving the path planning performance of robot in dynamic and complex environment is an important development direction of mobile robot intelligence. In this research, based on the idea of hybrid path planning, whale optimization algorithm is introduced combined with computer perception technology to realize the path planning of robot. In order to improve the performance of the traditional whale optimization algorithm, it is optimized and improved by genetic algorithm. Through the performance simulation analysis of the improved whale optimization algorithm, it can be seen that the improved algorithm has better path optimization performance and significantly improved efficiency compared with other traditional algorithms. It can perceive and calculate an optimized path.

Keywords: whale algorithm, robot, path planning, genetic algorithm, computer perception

1. Introduction

The intelligent obstacle avoidance and path planning technology of robot are hot topics in the development of robot field. The application of robot in various industries is more and more in-depth, which has greatly changed people's production mode and living standard. With the continuous development of science and technology, traditional industrial robots have been difficult to meet people's needs for industrial production and life, and people's demand for robot intelligence is becoming more and more obvious (Chen & Liu, 2019; Gao et al., 2020; Han, 2019; Xue et al., 2018; Wang et al., 2019). In the development of robot intelligence, path planning is a very important research direction, which is also an important development branch of artificial intelligence, with the characteristics of complexity and nonlinearity. The working environment of the robot is often full of uncertainty. When the robot wants to work normally in a complex environment, it must have a strong ability to search for environmental information, be able to accurately identify and recognize different environmental information, and be able to realize intelligent path planning in a complex dynamic environment (Azpurua et al., 2018; Hao & Yan, 2018; Sangiovanni et al., 2020).

As a new algorithm, hyperheuristic algorithm provides a high-level strategy to obtain a new heuristic algorithm. At the problem domain level, it uses the background knowledge of the expert field to define the problem and evaluate the function. The optimization characteristics of heuristic algorithm can be used to realize the path optimization of robot. In the functional field of computer, nonparametric statistics are more and more widely used. Derrac et al. (2011) systematically reviewed the current nonparametric programs and put forward some precautions and suggestions to guide the implementation of nonparametric statistics. A. W. Mohamed and others proposed a new compilation strategy to improve the superior performance of the difference scheme (DE). The variation strategy has better exploration ability and utilization ability. It can be seen from the numerical experimental analysis of ece2017 and ece2010 that the improved strategy proposed by them has slightly good robustness and stability, and the solution quality is also good (Mohamed et al., 2019).

At present, there are many common robot path planning methods, including ant colony algorithm, fuzzy logic method, artificial potential field method, etc. However, a single path planning method has great limitations in dealing with different environments, so many scholars have proposed a hybrid path planning method. In the complex and dynamic environment, the hybrid path planning method can realize the functional navigation of the robot and the functions given by the robot. At present, the most common two-layer structure mode is local path planning and global path planning (Liang et al., 2020; Mrudul et al., 2018; Zhao et al., 2020). The robot collects the surrounding environment information through the airborne sensors, realizes the global path planning according to the environment information, and issues the corresponding movement instructions to the robot to avoid obstacles (Fareh et al., 2019; Han & Yu, 2020). This research is based on the hybrid path planning method to carry out the robot path intelligent planning, optimize and improve the whale algorithm, and introduce the genetic algorithm to reduce the running time, which can achieve the higher algorithm accuracy and the best path planning effect.

*Corresponding author: Jie Zan, College of Mechanical and Electrical Engineering, Xi'an Polytechnic University, China. Email: zjwjcool@163.com.

2. Optimization Algorithm

Whale optimization algorithm is a typical biological simulation algorithm, which is a strategy simulation based on the search, attack, and encirclement behavior of humpback whales (Ayawli et al., 2019; Islam et al., 2021; Lazarowska, 2019). According to the whale predation search strategy, the whale optimization algorithm can achieve multiple iterations to obtain the optimal solution without worrying about the loss of search in large-scale networks. In the optimization algorithm, individuals in the group are regarded as search particles synchronized with other individuals. According to the principle of nearest selection, whales will find the best prey in the group and constantly update their position according to the established rules. Humpback whales will approach the target and carry out predation behavior according to the updated location. Let the current whale position be $X(j)$, the best whale position be $X^*(j)$, and j is the number of iterations. The whale position update function is expressed as

$$X(j+1) = X(j) - A \cdot D \tag{1}$$

$$D = |C \cdot X^*(j) - X(j)| \tag{2}$$

In the formula, A,C is the coefficient variable, and its calculation formula is

$$\begin{aligned} A &= 2a \times r - a \\ C &= 2r \end{aligned} \tag{3}$$

where a is a decreasing constant with a value range of [0,2], its expression is $a = 2 - \frac{2j}{M}$, r is a random number within [0,1], and M is the maximum number of iterations.

In the process of hunting, humpback whales will continue to narrow the encirclement, and the value of a will continue to decrease. When the value of A is reduced to the range of $[-1,1]$, whales can determine the relationship between their position and the target position. Further, the target position is updated through the spiral position, and the distance between the optimal position of the I-th whale and the target position is D', which is expressed as:

$$X(j+1) = D'e^{bl}\cos(2\pi l) + X^*(j) \tag{4}$$

$$D' = \left|X_j^* - X_j\right| \tag{5}$$

where j is a random number in the range of $[-1,1]$, and b is a constant of logarithmic spiral shape. During whale hunting, the capture range is continuously compressed through spiral circulation. The whale position update threshold is set as 50% probability, and its expression is

$$X(j+1) = \begin{cases} Xj - A \cdot D & p < 0.5 \\ D'e^{bl}\cos(2\pi)l + X(j) & p \geq 0.5 \end{cases} \tag{6}$$

where p is a random number in the range of $[0,1]$.

When the humpback whale reaches the predation range, it will carry out random predation. When the value of A is in the range of $[-1,1]$, it will be updated randomly through D. The whale will search the nearest prey to realize the global search function. Let the random individual position in the whale population be X_{rand}, and the formula of whale random predation is

$$\begin{aligned} D &= |C \cdot X_{rand} - X(j)| \\ X(j+1) &= X_{rand} - A \cdot D \end{aligned} \tag{7}$$

3. Path Planning Technology of Improved Whale Optimization Algorithm Based on Genetic Algorithm

Introducing genetic algorithm to improve whale optimization algorithm can realize the optimization of chromosome population in genetic algorithm, improve population quality, and finally find the optimal solution. The general idea is as follows: after each iteration of the algorithm, set the head whale in the whale as immigration, and then replace the worst chromosome in the chromosome. This can solve the problems of long time-consuming traditional algorithms, unstable local optimal solutions and optimization results, and finally improve the accuracy of path optimization. The steps are:

Step 1: An initial population is randomly generated, the number of individuals in the population is N, the initial parameters of genetic algorithm and whale optimization algorithm are set, and the starting position of the mobile robot is set.
Step 2: Randomly generate whale population size and corresponding location, and initialize parameters such as a,A,T.
Step 3: Calculate the fitness values of all individuals in the whale population to determine the optimal whale individual X^*.
Step 4: Update the position of each whale and select the position update formula according to the size of P value.
Step 5: Continue to calculate all whale populations until the optimal individual and corresponding position are calculated.
Step 6: Judge whether the maximum number of iterations of the algorithm is satisfied. If so, it ends. If not, go to step 2 to continue the iteration cycle of the algorithm.
Step 7: Cross mutation operation.
Step 8: The fitness function values of all individuals in the population are calculated according to the fitness values.
Step 9: Judge whether the termination conditions are met. If not, go to step 5 to continue the iterative cycle of the algorithm.
Step 10: The final optimization result is output and the algorithm ends.

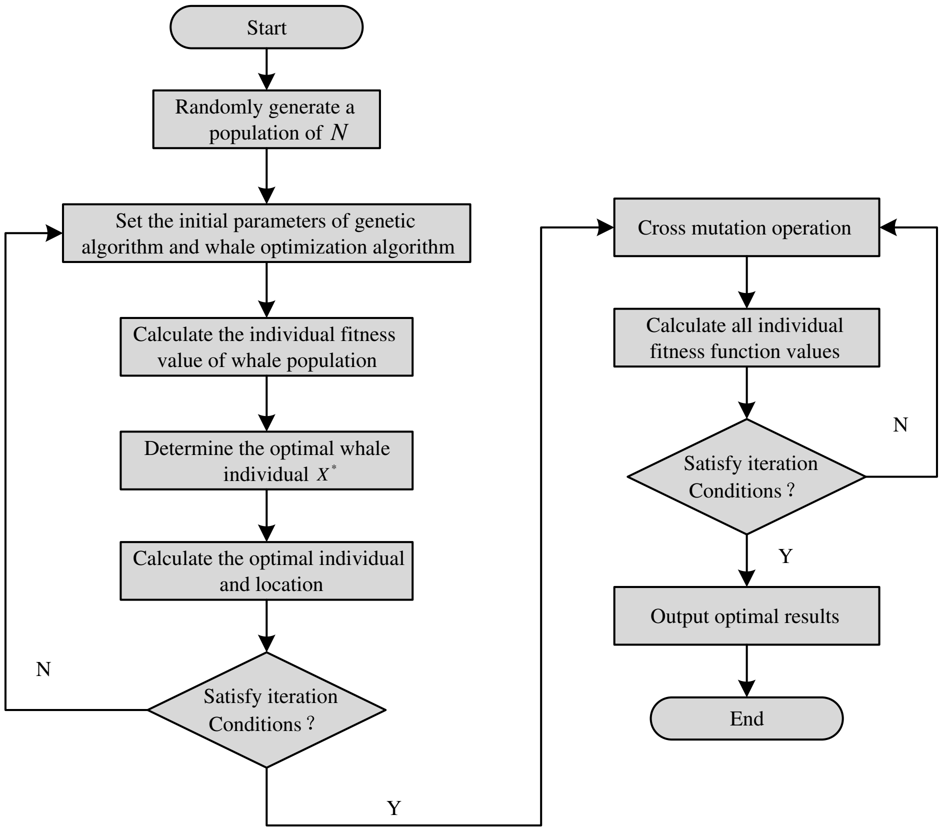
The improved algorithm flow chart is shown in Figure 1.

4. Design of Perception Technology for Logistics Robot

In order for logistics mobile robots to realize intelligent path planning, they must have the ability to perceive the environment, judge their own state and the external environment through the robot perception system, and then respond to the environmental changes as needed. In general, the workflow of mobile robot's environment sensing system mainly includes the following steps: first, use the robot's airborne sensors to collect environmental information and build and continuously update the environmental model; second, the mobile path is planned according to the constructed environmental model, and the robot is controlled to move; third, show the environment map perceived by the robot (Guo et al., 2021; Zhang et al., 2021).

Sensors are the source of information for the logistics robot to build the environmental model. The sensors for sensing the external environment mainly include infrared sensors, tactile sensors, visual

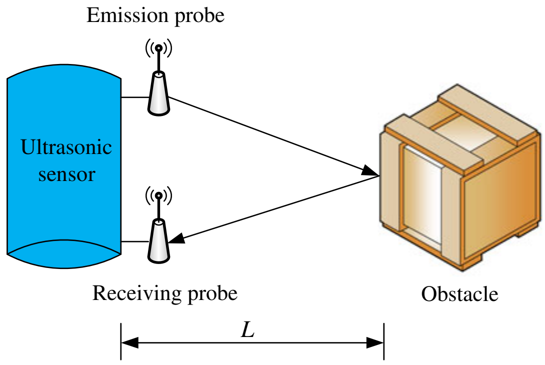
Figure 1
Flow chart of improved whale optimization algorithm



sensors, microwave radar, etc., and the sensors for determining the robot's own position mainly include speedometer, accelerometer, odometer, etc. (Zhong et al., 2020) For logistics robot, its speed and position are very important information. In this study, ultrasonic sensor is selected to collect information. Its basic principle is shown in Figure 2.

In Figure 2, L shows the distance between the sensor installed by the robot and the obstacle detection. Let the propagation speed of sound in the air be V, the time difference between the time when the sensor transmits the ultrasonic signal and the time when the sensor receives the signal be t, and the calculation formula of L is

Figure 2
Schematic diagram of basic principle of ultrasonic ranging of logistics robot



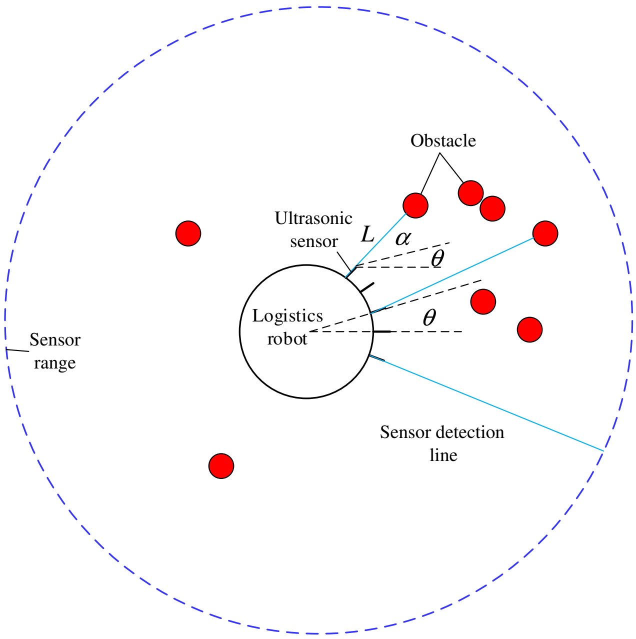
$$L = V \cdot t/2 \tag{8}$$

In the work of logistics robot, it is necessary to realize the perception of the surrounding environment through multiple sensors. When they work together, the sensors may interfere with each other. In order to solve this problem, the sensors need to be grouped and segmented to work (Derrac & García, 2011; Jiang & Xin, 2019; Wang et al., 2019; Zhang et al., 2021). With this working mode, although the time required in a round of environmental information collection will increase, compared with the time required for the operation decision-making of the robot, it can be ignored.

The common representation methods of environmental model include geometry method, topology method, grid method, etc.; according to the work needs of logistics robot, the grid method is selected to build the environmental model currently. In the constructed grid environmental model, each small grid will be given a nonnegative value to indicate the possibility of occupation, which is the obstacle confidence. The parameter update of the environmental model is shown in Figure 3. Multiple ultrasonic sensors on the logistics robot will send out detection lines in groups and periods and detect the distance between obstacles and sensors within the range.

(x,y,θ) is used to represent the position of the robot, where θ represents the orientation of the robot. In the environmental model, the installation angle α_i of the i sensor compared with the robot can form a quaternion vector (x, y, θ, α_i). The formula for mapping the data obtained by the sensor to the environmental model is

Figure 3
Environment renewal model of logistics robot



$$\begin{cases} x_m = x_r + (R_i + L_i) \cdot \cos(\theta + \alpha_i) \\ y_m = y_r + (R_i + L_i) \cdot \sin(\theta + \alpha_i) \\ map_{[x_m][y_m]} = map_{[x_m][y_m]} + 1 \end{cases} \tag{9}$$

where R_i represents the distance between the center point of the robot and the i-th sensor. The information of the obstacle distance returned by the sensor is L_i, (x_m, y_m) is the mapping coordinate point of the distance information, and $map_{[x_m][y_m]}$ is the obstacle confidence.

5. Analysis of Simulation Results

5.1. Path simulation analysis

In order to verify the comprehensive performance of the improved whale optimization algorithm, it is simulated and analyzed with the traditional whale optimization algorithm. When using MATLAB software for simulation analysis, first set up a 20×20 grid environment model. See Table 1 for parameter settings.

The optimal search paths for the two algorithms are shown in Figures 4 and 5, respectively, in which the upper left corner is the initial position of the robot and the lower right corner is the target position. Through the comparative analysis of the two diagrams, it can be seen that compared with the traditional whale optimization algorithm, the improved whale optimization algorithm can get a better planning path.

Table 1
Simulation environment settings

Parameter name	Value	Parameter name	Value
M	100	T	100
pc	0.8	M_1	100
pm	0.05	T_1	100

5.2. Comparative analysis of algorithm performance

The fitness function curves of GSK algorithm, AGSK algorithm, APGSK algorithm, whale algorithm, genetic algorithm, and the improved optimization algorithm based on genetic algorithm are compared and analyzed. The simulation results are shown in Figure 6. As can be seen from Figure 6, compared with the traditional whale algorithm, the state of the improved whale optimization algorithm tends to be stable at the third iteration, while the state of the traditional whale algorithm is more stable at the 18th iteration.

In order to further verify the comprehensive performance of the proposed improved algorithm, APGSK algorithm (Mohamed et al., 2021) and DE algorithm (Mohamed et al., 2018) are introduced for comparative simulation analysis. The three algorithms are simulated for 20 times to obtain the comparative analysis of path length and solution time. The analysis results are shown in Table 2.

As can be seen from Table 1, in the 20 simulations of the algorithm proposed in this paper, the average path length is 26.51 and the consumption time is 17.55. The average path lengths of APGSK algorithm and DE algorithm are 27.23 and 27.86, respectively, and the average consumption time is 18.41 s and 118.47 s. Further analysis shows that compared with APGSK algorithm and DE algorithm, the path length of the improved algorithm is optimized by 2.64% and 4.83%, and the consumption time is reduced by 4.64% and 4.98%. Comprehensive analysis shows that the optimization algorithm proposed in this paper has better application effect.

5.3. Nonparametric statistical test

In order to further test the comprehensive performance of the proposed algorithm, the nonparametric statistical test method is selected to verify the optimization performance of the proposed algorithm through Quade test, and the comprehensive evaluation is realized by calculating the T_j and S_j values of multiple algorithms. The smaller the total value, the smaller the corresponding algorithm.

Let i be the range in the group. Compared with the same optimization problem, the relative size of the observed value in the group is $S_{i,j}$, the range value arrangement rank of each data is Q_i, and the average rank is $\frac{k+1}{2}$, so:

$$S_{i,j} = Q_i \left[r_{i,j} - \frac{k+1}{2} \right] \tag{10}$$

The calculation formula of S_j as the total value is

$$S_j = \sum_{i=1}^{n} S_{i,j} \tag{11}$$

Let the optimization results of all algorithms rank from 1 to k as $r_{i,j}$. If the average rank is not considered, there are:

$$W_{i,j} = Q_i \left[r_{i,j} \right] \tag{12}$$

Further calculate the total value T_j of algorithm j:

$$T_j = \frac{W_j}{n(n+1)/2} \tag{13}$$

The calculation formula of W_j in equation (12) is

$$W_j = \sum_{i=1}^{n} W_{i,j} \tag{14}$$

The simulation analysis results of the average best quality and variance of the six algorithms are shown in Table 3:

Figure 4
Path simulation diagram of traditional whale optimization algorithm

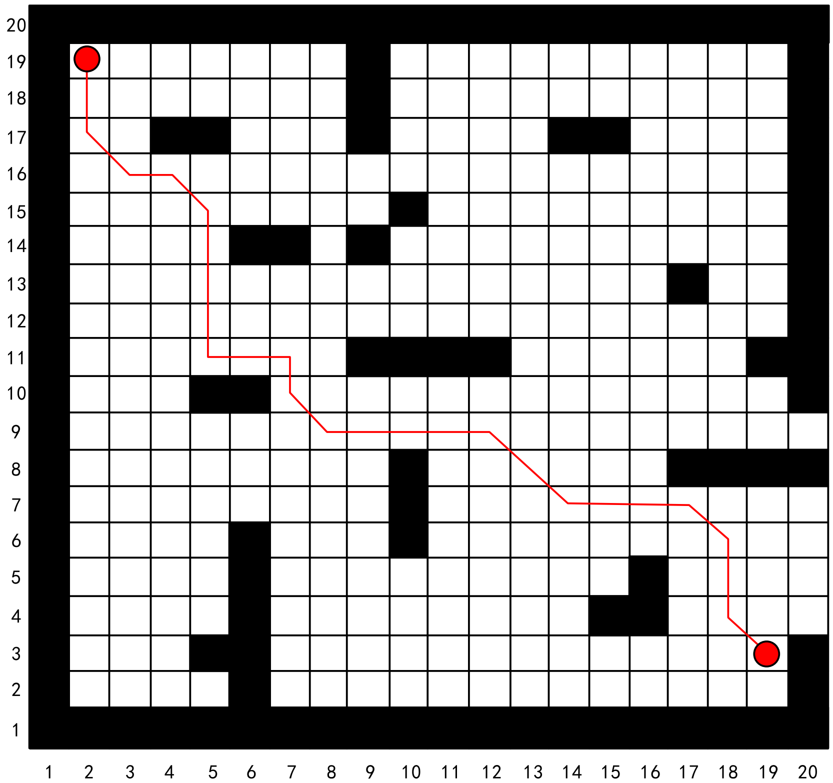


Figure 5
Path simulation diagram of improved whale optimization algorithm based on genetic algorithm

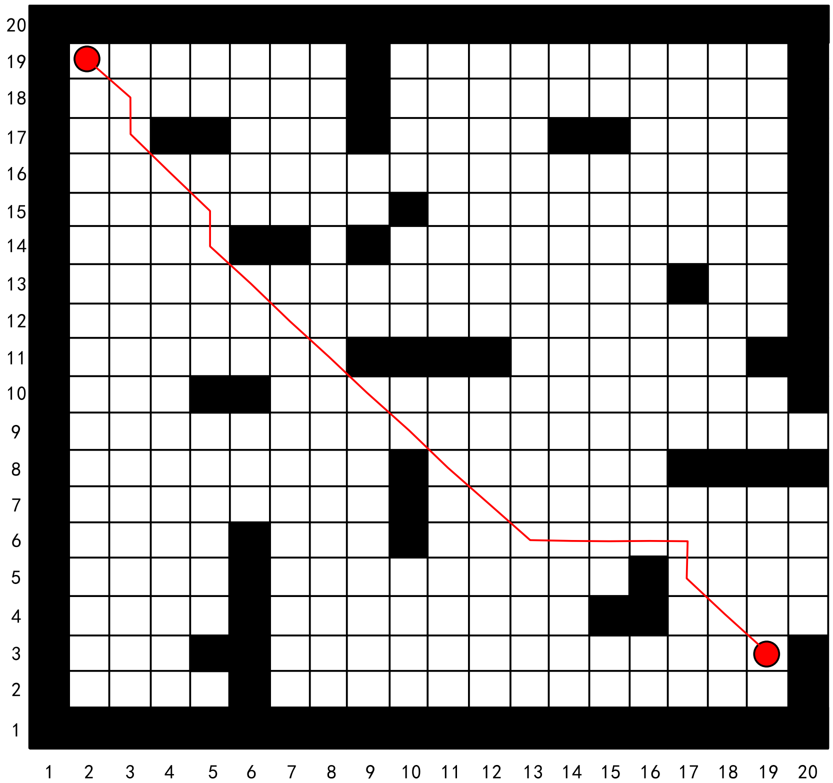
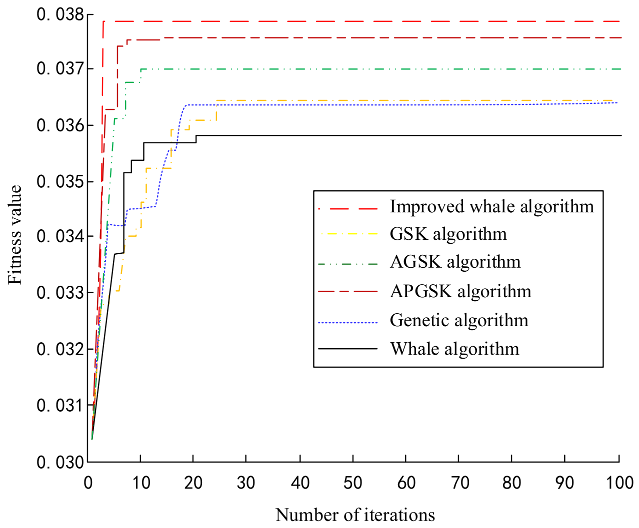


Figure 6
Comparison diagram of fitness function curve



It can be seen from Table 3 that the improved whale algorithm based on genetic algorithm has better convergence speed and search accuracy, and the comprehensive performance of the algorithm is the best, followed by APGSK algorithm, AGSK algorithm and GSK algorithm, while the comprehensive performance of genetic algorithm (GA) and traditional whale algorithm (WOA) is the worst.

6. Conclusion

In this study, a robot path planning method based on genetic algorithm and improved whale optimization algorithm is proposed to deal with the intelligent obstacle avoidance function of mobile robot in complex dynamic environment. According to the functional needs of logistics robot, the perception technology of logistics robot is studied and analyzed, and the grid method is proposed to build the environmental model. In order to verify the comprehensive performance of the improved algorithm, through simulation and comparison with the traditional whale optimization algorithm, it can be seen that the improved whale optimization algorithm has a better planning path and tends to be stable after the third iteration, and the efficiency of the improved algorithm is improved by 10.71%. After

Table 2
Comparative simulation analysis of path length and time consumption of three algorithms

	This paper improves the algorithm		APGSK		DE	
Number of runs	Path length	Solution time	Path length	Solution time	Path length	Solution time
1	26.18	17.35	27.32	18.11	27.15	18.55
2	26.44	17.28	27.15	18.02	27.64	18.16
3	26.73	17.46	26.82	18.24	27.56	18.43
4	26.14	17.94	27.54	18.36	28.04	18.75
5	26.83	17.08	26.97	18.65	27.96	18.08
6	26.35	17.84	26.88	18.75	27.64	18.46
7	26.16	17.54	27.34	18.46	27.15	18.06
8	26.44	17.57	27.66	18.20	28.14	18.76
9	26.98	17.10	27.18	18.17	28.06	18.78
10	26.52	17.87	27.37	18.47	28.57	18.55
11	26.02	17.64	27.08	18.64	27.64	18.31
12	26.34	17.54	27.81	18.77	27.66	18.07
13	26.77	17.98	27.31	18.02	27.54	18.47
14	26.96	17.99	27.00	18.73	27.53	18.96
15	27.02	17.47	26.97	18.17	28.31	18.54
16	26.84	17.58	26.93	18.94	28.05	18.73
17	26.18	17.92	27.15	18.64	28.64	18.52
18	26.46	17.43	27.33	18.24	28.25	18.15
19	26.34	17.28	27.48	18.08	28.43	18.47
20	26.52	17.17	27.32	18.44	27.15	18.64
Average value	26.51	17.55	27.23	18.41	27.86	18.47

Table 3
Analysis of Quade test results of various algorithms

Ranks		GA-WOA	APGSK	AGSK	GSK	GA	WOA
R_{mean}	S_j	2.745+001	2.762+004	3.042+015	3.241+044	3.55+054	3.745+005
	T_j	−1.912+020	−1.877+0.24	5.748+043	5.942+014	6.15+019	2.741+0.24
R_{Std}	S_j	2.847+001	2.894+014	2.735+011	2.713+018	2.74+004	3.142+003
	T_j	−8.143+015	−4.174+011	−2.246+025	−2.59+016	−2.721+025	2.816+019

comparing DE algorithm and APGSK algorithm for 20 times of simulation analysis, it can be seen that compared with APGSK algorithm, the path length and consumption time of the algorithm proposed in this paper are optimized by 2.64% and 4.64%, respectively, and compared with DE algorithm, the path length and consumption time of the algorithm proposed in this paper are optimized by 4.84% and 4.98%, respectively, indicating that the optimization algorithm in this paper has better path planning optimization performance. The simulation analysis is a model condition in a limited environment. Subsequent research can carry out field simulation analysis based on the robot developed by the improved algorithm proposed in this research.

Acknowledgement

This work was sponsored by Key R & D projects of Shaanxi Provincial Department of science and technology (Project NO: 2020GY-172); Science and technology guiding project of China Textile Industry Federation (Project NO: 2020109).

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

References

Ayawli, B., Mei, X., Shen, M., *et al.* (2019). Mobile robot path planning in dynamic environment using Voronoi diagram and computation geometry technique. *IEEE Access*, *7*, 86026–86040. https://doi.org/10.1109/ACCESS.2019.2925623.

Azpurua, H., Freitas, G. M., Macharet, D. G., *et al.* (2018). Multi-robot coverage path planning using hexagonal segmentation for geophysical surveys. *Robotica*, *36*(8), 1–23. https://doi.org/10.1017/S0263574718000292

Chen, G., & Liu, J. (2019). Mobile robot path planning using ant colony algorithm and improved potential field method. *Computational Intelligence and Neuroscience*, *2019*(b), 1–10. https://doi.org/10.1155/2019/1932812

Derrac, J., García, S., *et al.* (2011). A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm & Evolutionary Computation*, *1*(1), 3–18. https://doi.org/10.1016/j.swevo.2011.02.002.

Fareh, R., Baziyad, M., Rahman, M. H., *et al.* (2019). Investigating reduced path planning strategy for differential wheeled mobile robot. *Robotica*, *38*(2), 235–255. https://doi.org/10.1017/S0263574719000572.

Guo, N., Li, C., Wang, D., *et al.* (2021). Local path planning of mobile robot based on long short-term memory neural network. *Automatic Control and Computer Sciences*, *55*(1), 53–65. https://doi.org/10.3103/S014641162101003X.

Gao, L., Liu, R., Wang, F., *et al.* (2020). An advanced quantum optimization algorithm for robot path planning. *Journal of Circuits, Systems and Computers*, *29*(08), 2050122–143. https://doi.org/10.1142/S0218126620501224.

Han, F. (2019). Path planning algorithm for a mobile robot - A comparative study in different environment. *International Journal of Electronics Engineering Research*, *11*(2), 163–170. https://serialsjournals.com/abstract/53577_ch_55_-_path_planning.pdf

Han, S. D., & Yu, J. (2020). DDM: Fast near-optimal multi-robot path planning using diversified-path and optimal sub-problem solution database heuristics. *IEEE Robotics and Automation Letters*, *5*(2), 1350–1357. https://doi.org/10.1109/LRA.2020.2967326.

Hao, B., & Yan, Z. (2018). Recovery path planning for an agricultural mobile robot by Dubins-Rrt* algorithm. *International Journal of Robotics & Automation*, *33*(2), 202–207. https://doi.org/10.2316/Journal.206.2018.2.206-5443

Islam, M. R., Protik, P., Das, S., *et al.* (2021). Mobile robot path planning with obstacle avoidance using chemical reaction optimization. *Soft Computing*, *2021*(10), 1–28. https://doi.org/10.1007/s00500-021-05615-6

Jiang, J., & Xin, J. (2019). Path planning of a mobile robot in a free-space environment using Q -learning. *Progress in Artificial Intelligence*, *8*(1), 133–142. https://doi.org/10.1007/s13748-018-00168-6.

Lazarowska, A. (2019). Discrete artificial potential field approach to mobile robot path planning - ScienceDirect. *IFAC-PapersOnLine*, *52*(8), 277–282. https://doi.org/10.1016/j.ifacol.2019.08.083.

Liang, X., Kou, D., & Wen, L. (2020). An improved chicken swarm optimization algorithm and its application in robot path planning. *IEEE Access*, *8*, 49543–49550. https://doi.org/10.1109/ACCESS.2020.2974498.

Mohamed, A. W., Hadi, A. A., & Jambi, K. M. (2018). Novel mutation strategy for enhancing SHADE and LSHADE algorithms for global numerical optimization. *Swarm and Evolutionary Computation*, *50*, 100455. (EBLSHADE algorithm). https://doi.org/10.1016/j.swevo.2018.10.006.

Mohamed, W., Abutarboush, H. F., Hadi, A. A., & Mohamed, A. K. (2021). Gaining-sharing knowledge based algorithm with adaptive parameters for engineering optimization. *IEEE Access*, *9*, 65934–65946. https://doi.org/10.1109/ACCESS.2021.3076091.

Mrudul, K., Mandava, R. K., & Vundavilli, P. R. (2018). An efficient path planning algorithm for biped robot using fast marching method. *Procedia Computer Science*, *133*, 116–123. https://doi.org/10.1016/j.procs.2018.07.015.

Sangiovanni, B., Incremona, G. P., Piastra, M., *et al.* (2020). Self-configuring robot path planning with obstacle avoidance via deep reinforcement learning. *IEEE Control Systems Letters*, *5*(2), 397–402. https://doi.org/10.1109/LCSYS.2020.3002852.

Wang, X., Yan, Y., & Gu, X. (2019). Spot welding robot path planning using intelligent algorithm. *Journal of Manufacturing Processes*, *42*(June), 1–10. https://doi.org/10.1016/j.jmapro.2019.04.014.

Wang, C., Cheng, J., Chi, W., *et al.* (2019). Semantic-aware informative path planning for efficient object search using mobile robot. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *51*(8), 5230–5243. https://doi.org/10.1109/TSMC.2019.2946646.

Xue, H., Shao, Z. P., Pan, J. C., *et al.* (2018). Cultural firefly algorithm for dynamic path planning of soccer robot. *Kongzhi yu Juece/Control and Decision*, *33*(11), 2015–2020. https://doi.org/10.13195/j.kzyjc.2017.0821

Zhang, S., Pu, J., & Si, Y. (2021). An adaptive improved ant colony system based on population information entropy for path planning of mobile robot. *IEEE Access*, *9*, 24933–24945. https://doi.org/10.1109/ACCESS.2021.3056651.

Zhang, Z., Qiao, B., Zhao, W., *et al.* (2021). A predictive path planning algorithm for mobile robot in dynamic environments based on rapidly exploring random tree. *Arabian Journal for Science and Engineering*, 1–10. https://www.springerprofessional.de/en/a-predictive-path-planning-algorithm-for-mobile-robot-in-dynamic/18912470

Zhao, M., Lu, H., Yang, S., *et al.* (2020). The experience-memory q-learning algorithm for robot path planning in unknown environment. *IEEE Access*, *8*, 47824–47844. https://doi.org/10.1109/ACCESS.2020.2978077.

Zhong, X., Tian, J., Hu, H., *et al.* (2020). Hybrid path planning based on safe A* algorithm and adaptive window approach for mobile robot in large-scale dynamic environment. *Journal of Intelligent & Robotic Systems*, *99*(1), 65–77. https://doi.org/10.1007/s10846-019-01112-z.

How to Cite: Zan, J. (2022). Research on Robot Path Perception and Optimization Technology Based on Whale Optimization Algorithm. *Journal of Computational and Cognitive Engineering* 1(4), 201–208, https://doi.org/10.47852/bonviewJCCE597820205514