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WOA-AGA Algorithm Design for Robot Path Planning

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Abstract

Currently, mobile robot has great application value in industrial production. It can play a unique advantage in improving industrial production efficiency and saving industrial production costs. Path planning plays an important role in the performance of mobile robots. Therefore, to improve the path planning efficiency of mobile robots in complex environments, a path planning model combining genetic algorithm (GA) and whale optimization algorithm (WOA), namely WOA-AGA model, is proposed. In the model, the traditional GA model is introduced into the difference degree function. WOA makes up for the local optimization problem and the low proficiency of AGA algorithm. WOA-AGA effectively solves the problems of local optimization, long convergence time and unstable optimization results. The experiment is simulated in dynamic and static environment: AGA algorithm has 1.87% higher efficiency than GA algorithm; Compared with AGA algorithm, the overall operation efficiency of WOA-AGA algorithm is increased by 3.87%. Finally, two types of complex scenes are selected for path planning in the experiment. The results indicate that WOA-AGA algorithm can obtain shorter and more reasonable optimal path than other similar algorithms. From the perspective of improving the path planning effect of mobile robots, this study aims to obtain the best path through the reasonable application of WOA-AGA model to improve industrial production efficiency.

Keywords: Genetic algorithm, Whale optimization algorithm, Robot, Path planning, Grid method.

1 Introduction

With the acceleration of the industrialization process, the application field of robots is more and more extensive. In modern society, traditional industrial robots are increasingly unable to meet the growing needs of people [1]. The mobile robot belongs to the comprehensive high and new technology, and has a wide range of applications in industrial production. Among them, path planning has a profound impact on the work performance of robots and is a hot issue in the research of mobile robot perception [2]. As a method to solve problems, the most important features of path planning are constraints, complexity and nonlinearity [3]. The environment of mobile robots is usually uncertain and complex, so the perception ability of mobile robots is put forward higher requirements. In addition, mobile robots are prone to judgment confusion in a variety of dynamic, complex and hindered environments [4]. Currently, the path planning of mobile robots has become the focus of many researchers, and more scholars have tried to combine intelligent algorithms with path planning, and have launched a heated discussion on it. This way of thinking can significantly improve the efficiency of path planning, and is also the mainstream of current research. However, looking at the current research results, most path planning still has many problems such as local optimal solutions and unstable optimization results. Therefore, how to find the optimal robot transportation path in the shortest time is still an urgent problem to be solved. Genetic Algorithm (GA) and Whale Optimization Algorithm (WOA) are two classical intelligent optimization algorithms, which have good applicability in the process of robot path optimization [5]. Therefore, this study attempts to combine the two to build a WOA-AGA model to improve the adaptability of robots to plan paths in complex environments. The aim of this study is to optimize the path planning effect of mobile robots through the rational application of WOA-AGA model, so as to further improve the industrial production efficiency.

2 Related work

With the rapid development of intelligent technology, more and more people pay attention to robot path planning, which is discussed by many scholars. Chang L et al. study an improvement strategy using Q-learning to solve the problem that dynamic window method is easy to rely on global reference in path planning. This strategy can adaptively learn model parameters and obtain trained agents to adapt to the unknown environment. Although this model has excellent navigation capabilities in both static and dynamic environments, it takes a long time to navigate, thus affecting the overall industrial production efficiency [6]. Yang Y proposes to introduce Q network into multi-robot deep learning algorithms, focusing on the study of handling robots. This method combines Q algorithm and experiential playback mechanism to generate target Q value, which effectively solves the problem of slow convergence of traditional methods. The results show that the model can learn the path planning problem faster and improve the overall work efficiency of the robot. This study provides reference for the subsequent path planning of mobile robots, but its own shortcomings of easily falling into local optimal need to be further solved [7]. Wang B et al. study robot path planning under large-scale dynamic environment. Aiming at dynamic obstacles, they propose a global guided reinforcement learning method, which solves the disadvantage of the traditional reprogramming strategy's low overall operation efficiency. The method combines a novel reward mechanism that works effectively in any environment. It is verified that although the method has good generalization performance, its path planning effect does not reach the ideal state [8]. Based on the research in the field of large-scale transportation logistics, Li Qiang's team proposes a distributed path planning scheme using graph neural networks. The experiment incorporates a focus mechanism that allows message dependencies to improve traditional networks. This mechanism can determine the important characteristics of the information received from different neighboring robots. This model has good generalization effect in practical application, which is of enlightening significance for the study of intelligent algorithm combined with path planning in this paper [9]. Qi J et al. propose a new algorithm for robot navigation in dynamic and unfamiliar environments that combines multi-objective and fast exploration techniques. Considering the path length and smoothness, the algorithm can quickly identify the optimal node from many candidate nodes. The simulation results of the model in the dynamic environment show that it has excellent performance in avoiding obstacles, but its final planned path length is relatively long and the effect is mediocre [10].

Because of its good practical performance, intelligent algorithm has been widely used in various fields, which brings many opportunities for robot path planning. Wu Y et al. propose a hybrid UAV path planning algorithm combining distributed estimation algorithm and genetic algorithm. The algorithm can consider the requirements of different stages in the iterative process and realize the local adjustment strategy online. The simulation results of this study show that the proposed method can improve the efficiency of UAV task execution, but the problem of local extremum cannot be well optimized [11]. Hayat S et al. introduce GA algorithm into the path planning of UAV rescue mission, and on this basis propose two adaptive strategies. This strategy can optimize search, notification, monitoring tasks and adjust the priority of tasks in a timely manner. This strategy has certain effectiveness, but the traditional GA algorithm has not been optimized and improved, and the overall model still has problems of slow convergence and low efficiency [12]. Zhang Z et al. combine genetic algorithm with sparrow search to get the path planning of the robot, and proposed linear path strategy and neighborhood search strategy according to the running speed and convergence performance of the robot. In the experiment, a new comprehensive index evaluation method is designed to evaluate the proposed model, and its superior performance is verified. This study has certain reference significance for the WOA-AGA model proposed in this paper [13]. Zhou M's team designs a hybrid path planning model that combines improved WOA and Gray Wolf optimization algorithms. The model also introduces dynamic window method for local path planning. Finally, the feasibility and effectiveness of the method are verified by simulation experiments. This model can show good performance for local path planning, but fails to show proper coordination ability in complex environments [14]. Alabdalbari A and Abed introduce particle swarm optimization based on WOA algorithm to limit the planned path of robot collision in static environment. The results show that this method can follow the perfect path criterion and has excellent performance in path planning. This model has certain application value, but the overall model still has defects such as local optimal solution and unstable final optimization results [15].

In summary, robot path planning based on intelligent algorithm has made some progress in recent years. However, for robots with complex and difficult tasks, the existing path planning methods still cannot meet their work needs. In addition, most path planning models fail to provide appropriate solutions to problems such as local optimal solutions and unstable optimization results. Therefore, a path planning model is proposed, which combines WOA algorithm and AGA algorithm to realize the optimal path planning in different environments.

3 Research Model

3.1 Whale Optimization Algorithms and Genetic Algorithm Models

The classic GA algorithm simulates the genetic evolution mechanism of organisms, replacing genetic operations in the reproductive process with natural competition laws and genetic information. GA can enable individuals in the population to produce excellent individuals adapting to environmental changes through adaptive crossover and mutation under the effect of natural selection and genetic information. Due to its relatively simple content, easy implementation, and good search performance, GA has been successfully applied in many fields [16, 17]. In production scheduling, it can be used to optimize the selection of transportation methods, routes, and related equipment for raw materials and finished products during the production process. In data mining, it can be used to predict product demand and related equipment. In image processing, it can be used to segment and track image targets. These successful implementations have greatly promoted path planning research and application. GA's basic implementation process is shown below.

GA is a path search algorithm based on random iteration and evolution, which simulates genetic and biological laws, and its core idea is the natural law of survival of the fittest. To achieve the purpose of fast optimization, unsuitable factors are excluded during iteration. The specific steps of GA are: (1) coding the problem solution set. That is, the solution of the problem is expressed by chromosome, the initial population is obtained by chromosome form, and the fitness function of the

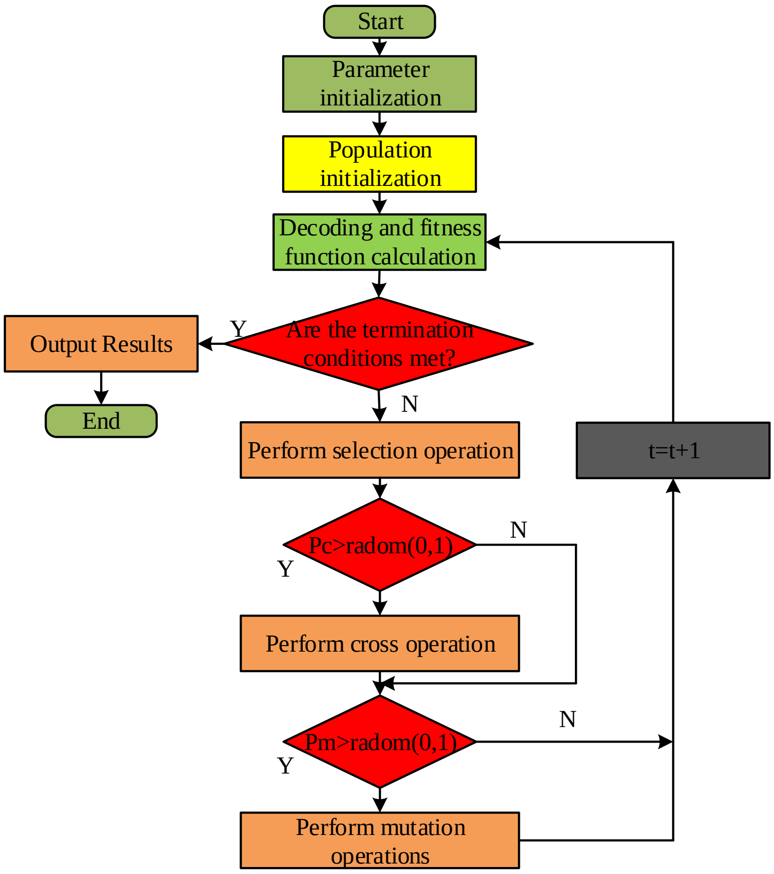


Figure 1: The Basic Process of GA Algorithm

algorithm is determined by the objective function of the optimization problem. (2) The participation of high-quality individuals in genetic manipulation is achieved through the analysis of fitness values. (3) Replace reproduction with the natural laws of competition and the contents of heredity until the best results are obtained. In this process, each individual has to evaluate their own degree of adaptation to determine their own degree of adaptation. In the process of selection, crossover and mutation, each individual can maintain its correct direction and get the optimal result. In GA algorithm, the nature of the initial population has a great influence on the performance of GA. This algorithm can generate feasible paths quickly, but it has some disadvantages such as low quality of initialization path and low efficiency of filtering rules. Therefore, this study will further improve the method to achieve a more suitable path selection [18]. The fitness function selected by GA will directly affect whether the optimal result can be obtained at last. Therefore, this study introduces the difference degree function into the GA algorithm, that is, to build the AGA model. AGA algorithm mainly optimizes its adaptability function to overcome the randomness and blindness of traditional genetic algorithm. The general fitness function expression is shown in equation (1) :

$$Fitness'_t = \sum_{l=1}^{N} \frac{F(l)}{F(t)} \tag{1}$$

In equation (1), N represents the number of individuals; $F(t)$ represents the maximum objective function value; $F(l)$ is the minimum objective function value. difference function Introduce here to meet the requirements of population diversity. Assuming the difference between two physical examinations is shown in equation (2):

$$\begin{aligned} D(i,j) &= \frac{1}{K} \sum_{l=1}^{K} (x_{ij} - x_{jl}) \quad i,j = 1,2,\ldots,n \\ x_{ik} - x_{jk} &= \begin{cases} 0 & x_{ik} = x_{jk} \\ 1 & x_{ik} \neq x_{jk} \end{cases} \end{aligned} \tag{2}$$

In equation (2), x_{ik}, x_{jk} represents the value of individual x_i, x_j in position k. The difference function represents the mean of the sum of differences between all individuals in the population except for individual t and t, as shown in equation (3):

$$D(t) = \frac{1}{N-1}\sum_{i \neq t}^{K} D(t,i) \quad i = 1, 2, \ldots, N \tag{3}$$

In equation (3), $D(t,i)$ represents the degree of difference between all individuals in the population except individual t and t, and the final fitness function is shown below:

$$Fitness_t = D(t)\sum_{l=1}^{N} \frac{F(l)}{F(t)} \tag{4}$$

Equation (4) is the fitness function of genetic algorithm by introducing the difference degree function. AGA can improve the randomness and blindness of GA transmission to some extent. However, it has its own precocious defects, and it is easy to fall into local optimal. Based on this, the study applied WOA algorithms to the new chromosomes produced during each generation of genetics. WOA is a heuristic algorithm that is mainly used to simulate the rounding, attacking, and searching of humpback whales during feeding. WOA treats all individuals in a group as searching particles that keep pace with others. It sets the location of the target as the closest distance to the target, and then selects an individual from a population as the best search particle according to the principle of closest. After that, other search particles will continue to update their position according to certain rules. A humpback whale will move as quickly as possible to get close to its target, or cooperate with the group to hunt. The algorithm is mainly to "exchange blood" on chromosomes to find the optimal solution, that is, to replace the original poor population and use the new excellent population to evolve. Combining WOA with AGA can make it have strong global optimization ability and local optimization ability. However, in the traditional WOA algorithm, the optimal advantage of the next iteration is often too dependent on the optimal advantage of the current iteration. Therefore, as shown in equation (5), the study introduces information-oriented strategies to make improvements:

$$Y^*(t) = w_3 Y_1(t) + w_2 Y_2(t) + w_1 Y_3(t) \tag{5}$$

In equation (5), $Y_1(t), Y_2(t), Y_3(t)$ represents the optimal position, suboptimal position, and more optimal position of the whale population when the number of iterations is t. w_1, w_2, w_3 represent the weights of $Y_1(t), Y_2(t), Y_3(t)$ when the number of iterations is t. Y represents the individual's position vector. Y^* is the optimal individual position in the current iteration. Equation (5) represents the WOA algorithm based on an information-oriented strategy, which enables the exchange of location information between individuals. The information guided predatory strategy enhances the exchange of positional information between individuals. However, when implementing predation, WOA does not include the positional effects of previous predatory individuals. This will cause omissions in the WOA algorithm during the solving process, reducing the convergence speed. This article proposes an improved Golden Synthetic approach to enhance whale predation strategies, as shown in equation (6):

$$Y(t+1) = Y(t) \cdot |\sin(Q_1)| + Q_2 \cdot \sin(Q_1) \cdot |x_1 \cdot Y^*(t) - x_2 Y_{mean}(t)| \tag{6}$$

In equation (6), $Y_{mean}(t)$ is the average position of all whale individuals in the population after t iterations. Q_1, Q_2 represents a random number. Among them, Q_1 affects the individual's movement distance, and Q_2 affects the individual's movement direction. x_1, x_2 represent the golden section coefficients. WOA introduces a convergence factor during iteration to adjust the convergence. However, in the classic WOA, this value is linearly reduced, resulting in a gradual decrease in the overall optimization performance of WOA. Therefore, this study adopts a nonlinear convergence coefficient represented in equation (7) to regulate:

$$a = \begin{cases} \dfrac{T_{\max}^2}{4}\left(\left(t - \dfrac{T_{\max}}{2}\right)^2 + 1\right), & t \leq \dfrac{T_{\max}}{2} \\ \dfrac{T_{\max}^2}{4}\left(t - \dfrac{T_{\max}}{2}\right)^2, & t > \dfrac{T_{\max}}{2} \end{cases} \tag{7}$$

In equation (7), $T_{\max}$ is iterations' maximum. a represents the convergence factor. This article adopts a combination of WOA and AGA, which first adopts WOA to imitate the predatory behavior of humpback whale populations, optimize the chromosome population, and improve population quality. Excellent genetic factors are optimized through the Whale Optimization Algorithm and then subjected to a series of genetic algorithm operations to ultimately find the optimal solution. The overall WOA-AGA implementation process is shown below.

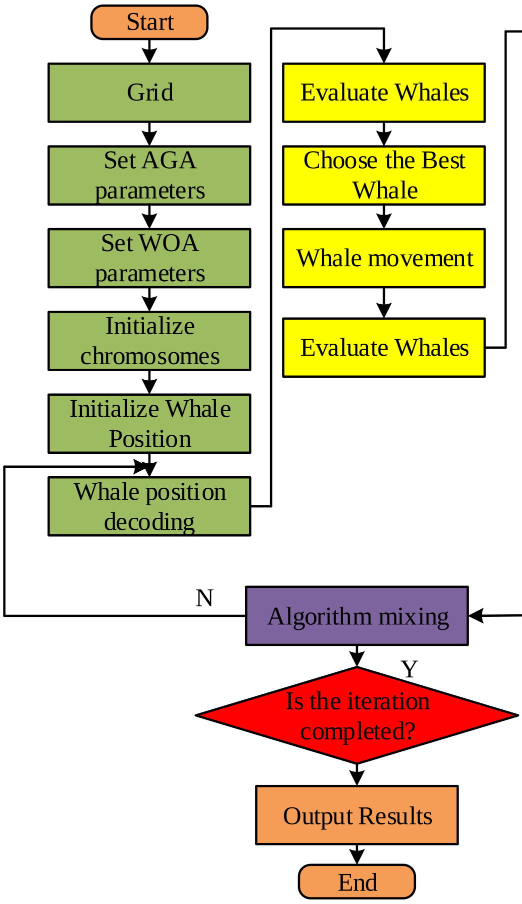


Figure 2: Implementation Process of WOA-AGA Model

3.2 A Robot Human Path Planning Model Integrating WOA-AGA Model

In response to the problems of local extremum, long convergence time, and unstable optimization results in traditional GA, this study proposes an improved WOA-AGA algorithm. It regards the mobile robot localization problem as a global optimization problem, selects a humpback whale from the whale population, migrates it to the chromosome of the genetic algorithm, and then replaces the humpback whale with the worst chromosome in the genetic algorithm. This not only effectively avoids the problems of local extremum, long convergence time, and unstable optimization results in traditional genetic algorithms, but also ensures that mobile robots can quickly find the target results in different environments. In addition, the WOA-AGA algorithm can avoid redundant operations and continuously optimize the optimal operator, thereby improving the solving accuracy of the genetic algorithm [19]. For robots' actual path planning, modelling their testing environment is needed. This study chooses to use grid method to establish the mobile environment of robots. This study uses grid modeling method to create a model, which can divide the robot's workspace into multiple 2D structured spaces, with identical grid dimensions. Throughout the path planning process, the robot can be viewed as a particle rather than a fixed three-dimensional entity. Meanwhile, robots can quickly determine the orientation of obstacle sizes [20, 21]. Figure 3 illustrates the representation of the environment model for the robot's workspace. The free space and obstacles are depicted as a collection of grid blocks, with shaded regions indicating the presence of obstacles.

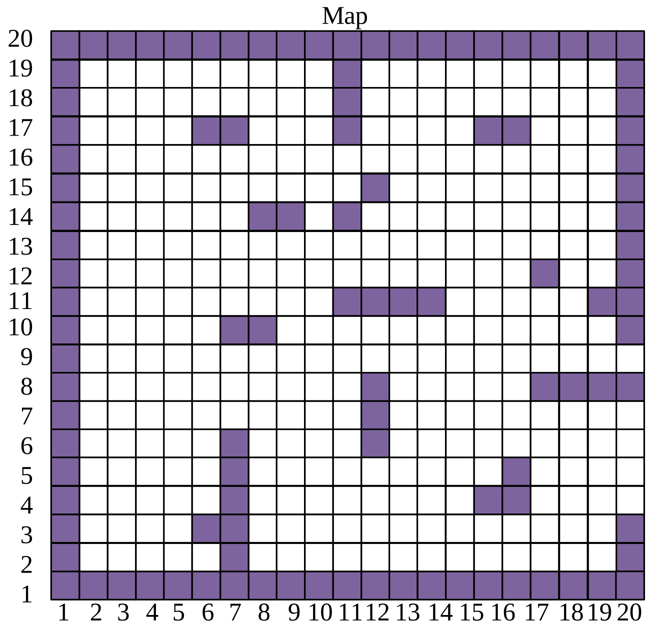


Figure 3: Experimental Environment Model

The grid is represented by serial number method and Cartesian coordinate system method, and the two methods can be converted to each other. The coordinate relationship of the grid S is shown in equation (8):

$$\begin{cases} x = \text{mod}(S-1, n) + 0.5 \\ y = n + 0.5 - \text{ceil}(S/n) \end{cases} \tag{8}$$

In equation (8), S represents the grid number. mod represents the remainder operation. ceil represents an upward rounding operation. $n \times n$ represents the grid size. Figure 4 shows a binary representation of the robot path.

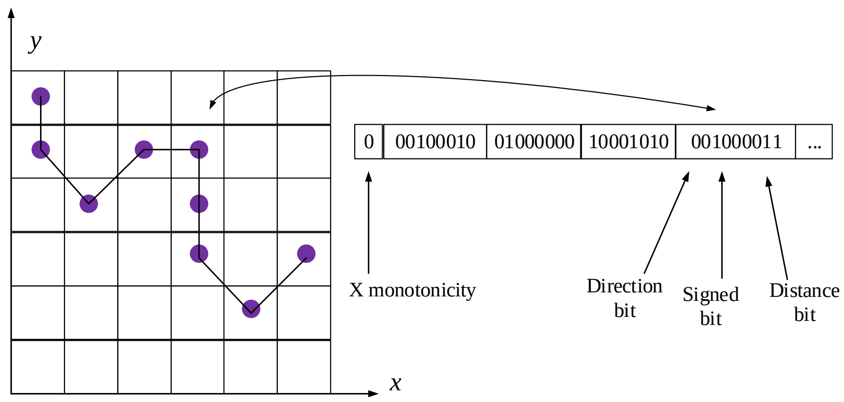


Figure 4: Binary Representation of Robot Path

When the path is discontinuous, filling it with adjacent free grid points to make it a continuous path without crossing any obstacles is called the insertion operator. The continuity of two adjacent grids is analyzed by the following equation (9):

$$\delta = \max\left\{abs\left(x_{i+1} - x_i\right), abs\left(y_{i+1} - y_i\right)\right\} \tag{9}$$

In equation (9), $x_{i+1}, y_{i+1}, x_i, y_i$ represent the Cartesian coordinate system of the two adjacent grids. abs represents absolute value. max represents the maximum value. When $\delta = 1$, it indicates that the two adjacent grids have continuity, otherwise there is none. When two grids do not have continuity, the average method can solve the inserted grid in equation (10):

$$x_i' = \text{int}\left[\frac{1}{2}\left(x_i + x_{i+1}\right)\right], y_i' = \text{int}\left[\frac{1}{2}\left(y_i + y_{i+1}\right)\right] \tag{10}$$

In equation (10), int represents the average interpolation method. At this point, p_i' an be expressed as equation (11):

$$p_i' = x_i' + y_i' \tag{11}$$

If the calculated number p_i' grid belongs to a free form grid, only the insertion needs to be filled in. And a non free mesh using the nearest free light mesh will be inserted. If it cannot be implemented, it is an infeasible path and the operator will be removed. This process is repeated until the individual becomes a continuous and feasible path. If it is a discontinuous free mesh path that has not been generated by the initial value, an operator can be inserted into the initial value to supplement it and make it continuous [22]. On this basis, using existing knowledge and experience, it can be known that individuals who complete initialization belong to feasible paths and do not need to apply penalty functions [23, 24] . This method greatly reduces the computational complexity and overall execution time of the algorithm. In the grid structure shown in Figure 3, its movement space can be represented by a planar Cartesian coordinate system [25, 26]. For robots, path optimization and trajectory tracking control problems can usually be described by multiple information containing n decision variables, as shown in equation (12):

$$\min F(x) = [f_1(x), f_2(x), \ldots, f_m(x)]^T \tag{12}$$

In equation (12), $F(x)$ represents the final fused information. $f_m(x)$ represents decision information for various variables. As a nonlinear system, robot should be linearized to achieve better trajectory tracking. Equation (13) represents robot's 2D motion space during this process:

$$V_2 = \{p(x, y) \mid x \in (0, width), y \in (0, height), x, y \in N\} \tag{13}$$

In equation (13), $width$ and $height$ represent the definition domain of coordinates. $p(x, y)$ represents the coordinates. Where width represents the horizontal coordinate and height represents the vertical coordinate. Robot's motion state parameters can be represented by equation (14):

$$x_k = f\{x_{k-1}, u_{k-1}, w_{k-1}\} \tag{14}$$

In equation (14), x_k represents the center displacement of the robot chassis. u_k represents the rotational inertia of the robot. w_k represents the measurement error during operation. The parameter measurement equation for robot motion trajectory is:

$$E[M_A] = E[V_A] = \sum_{i=0}^{\infty} i(1-p)^i p = (1-p)/p \tag{15}$$

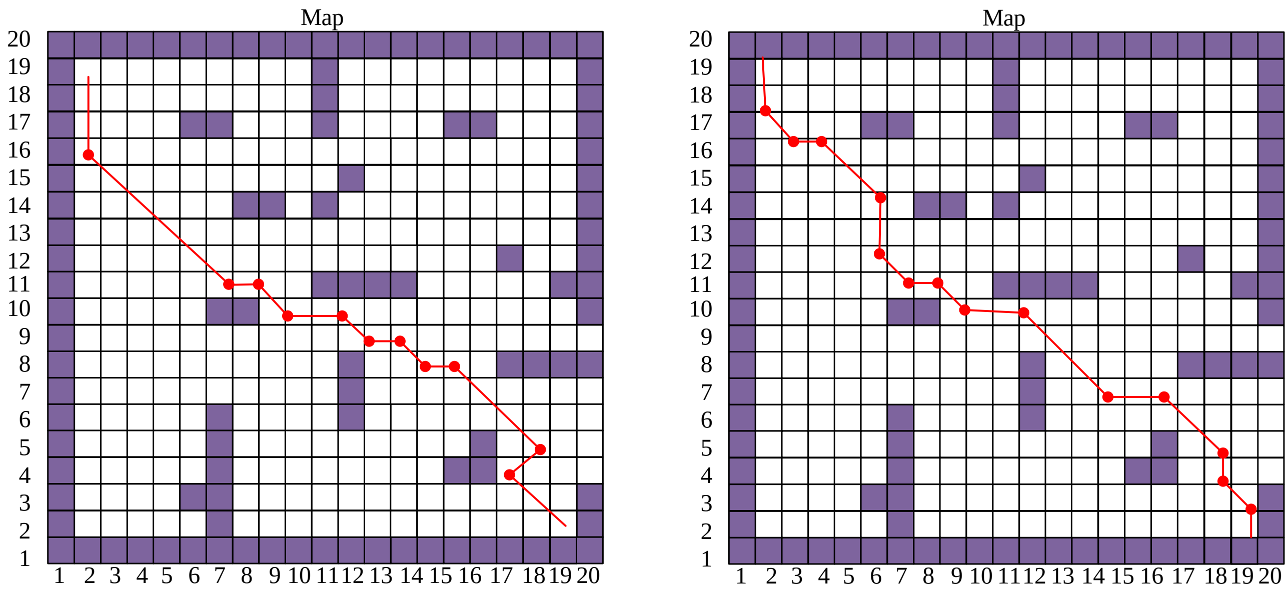
In equation (15), M represents the obstacle blocking the main direction during the robot's movement. V_A represents the measurement error generated. p represents the center of gravity of the robot. The hybrid WOA-AGA aims at the adaptability of mobile robot path planning to complex environments. This algorithm first utilizes AGA for global path planning, and integrates WOA into each step of the AGA operation process, selecting the optimal operator during this process. By implementing this approach, the algorithm's efficiency can be substantially enhanced and the issue of premature convergence can be mitigated. This optimization technique is capable of considerably improving the real-time performance of mobile robots' motion trajectory in complicated settings, and can effectively improve the quality of the motion trajectory. Afterwards, the experiment conducted simulation analysis on the proposed model. In this study, the performance of WOA-AGA model is evaluated from the length of the final planning path of the model, the solution time, the fitness curve of the algorithm itself and the change of the iteration curve.

4 Model validation and Results

4.1 Robot Path Simulation Analysis in Static Environment

Firstly, the effectiveness of AGA is verified. To better compare the feasibility and superiority of AGA for robot path planning, AGA and traditional GA methods are compared in the experiment.

This experiment uses the Ubuntu system and wireless network to control the mobile robot to complete the route planning. This paper takes the two-wheel drive car as the research object. The system adopts the control system such as obstacle avoidance radar and position and attitude sensor. The working process of the cart: First, the computer side controls the development board of the cart through wifi; Using the image data obtained by the camera and processing; Finally, the processed image is transmitted to the computer via the wireless network in the car. In the experiment, the STM32 is loaded on the trolley to realize the microcontroller of the mobile robot. A radar device is installed on the car to avoid obstacles, and the actual distance between the obstacles and the cart judged by the vision sensor is detected in real time. In addition, the three-axis sensing device can adjust the vehicle's position, speed and wheelbase in real time to achieve path planning goals to avoid collisions. The experiment environment is the grid of 20×20, and it is carried out in MATLAB software.The initial population size of GA algorithm is set to 100. The crossover probability is 0.8; The probability of variation was 0.05. The maximum number of iterations is 100. In the simulation experiment, the radius of the robot field of view is 1 cell; The speed is 1.5 cells per second; The safety threshold between the robot and the obstacle is 0.1 cells. SPSS 22.0 statistical software was used for data processing, and Mann-Whitney test was used for comparison between groups. Calibration level $a = 0.05$. If $P < 0.05$, the difference was statistically significant, and if not, there was no difference. The final path planning results of the traditional GA model and AGA algorithm are shown in Figure 5. The results in the figure show that AGA moves more steps and turns more times than GA, which improves the accuracy of robot path planning to a certain extent.



(a) GA Algorithm Path Simulation

(b) AGA Algorithm Path Simulation

Figure 5: Final Path Planning Results of GA Model and AGA Algorithm

Figure 6 shows the change comparison results of the fitness curve and iteration curve of the two algorithms. As shown in Figure 6(a), the GA algorithm complete the iteration around the 70th iteration, and the overall convergence rate is slow. AGA reaches a stable state in 18 iterations. Finally, the fitness value of AGA is higher, and its stable state is better than that of GA algorithm. In Figure 6(b), the GA algorithm cannot quickly find the direction of the target point in the early stage of the path optimization process, converging slowly. AGA accelerates convergence compared to the GA algorithm, but it also needs to be optimized for path selection, just like the GA algorithm.

To further verify the superiority of the AGA algorithm, 15 simulation experiments are conducted using both AGA and conventional GA models, and corresponding results are obtained in Table 1. Data shows that the average path value of GA algorithm 15 times is 27.8768, and the average time is 18.5491. The average AGA path value is 27.6643, and the average time is 18.4374. The operational efficiency of AGA has increased by 1.87% compared to GA. As a result, the AGA algorithm can achieve good performance in a short period of time, and is superior to traditional GA algorithms in terms

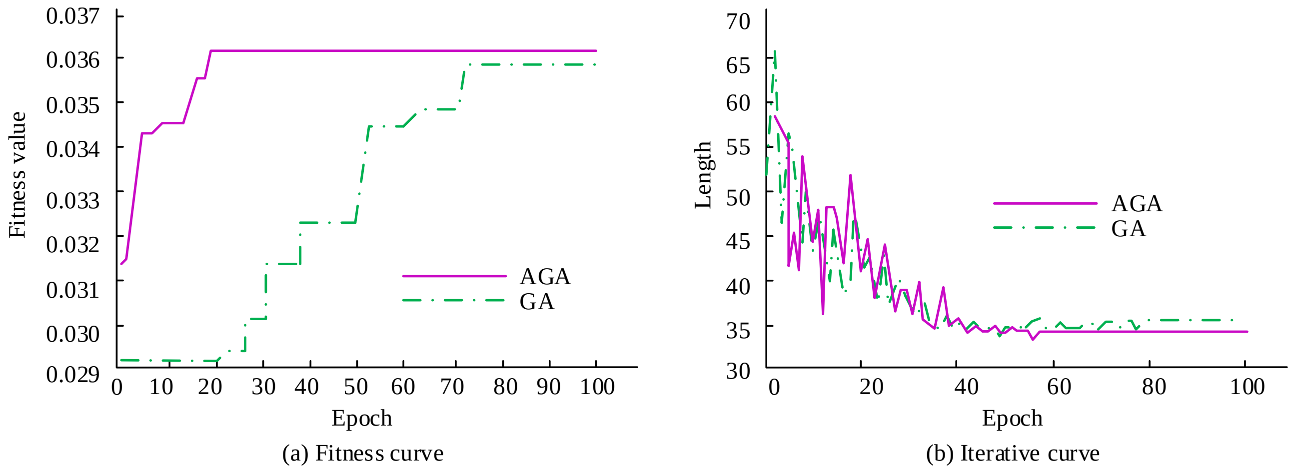


Figure 6: Change Results of GA and AGA's fitness Curves and Iteration Curves

Table 1: Path length and time obtained from 15 GA and AGA simulations

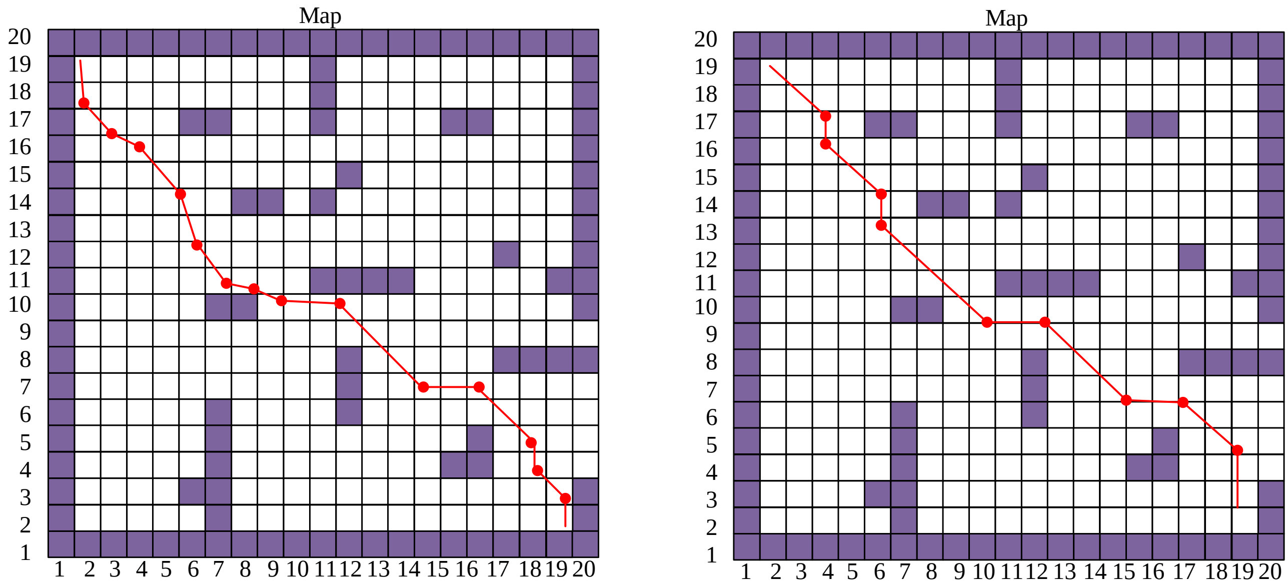
Number of runs	GA		AGA		P	
	Length	Time consuming	Length	Time consuming	Length	Time consuming
1	27.7869	18.5213	27.7856	18.4568	0.000	0.025
2	27.8845	18.4569	27.7745	18.3322	0.002	0.000
3	28.4596	18.7845	28.3214	18.6654	0.025	0.000
4	27.4587	18.2697	27.1247	18.1023	0.000	0.001
5	28.8974	18.5679	28.1236	18.4896	0.000	0.004
6	28.4789	18.6548	28.4652	18.5541	0.001	0.003
7	27.4587	18.6729	27.3541	18.6423	0.000	0.000
8	28.0123	18.6547	27.1456	18.5147	0.003	0.000
9	27.1456	18.9841	27.0012	18.8451	0.000	0.000
10	28.4791	18.8845	28.4012	18.8715	0.012	0.007
11	28.2156	18.4129	28.0123	18.3329	0.014	0.001
12	27.1458	18.4625	27.0002	18.3145	0.000	0.019
13	27.1236	18.5647	27.0015	18.4167	0.000	0.000
14	27.1485	18.2312	27.1214	18.0212	0.000	0.000
15	28.4569	18.1133	28.3322	18.0013	0.011	0.000

of stability and accuracy. The difference between the two algorithms is significant ($P < 0.05$), which verifies the effectiveness of introducing the difference degree function in the traditional GA algorithm.

To verify the feasibility and superiority of the WOA-AGA model in robot path planning, experiments are conducted to compare it with the AGA algorithm. The path planning results are shown below. It is not difficult to find from the figure that WOA-AGA combines the advantages of both WOA and AGA algorithms, reducing the number of robot steps and improving the efficiency of robot path planning. Thus, the validity of WOA-AGA model is verified.

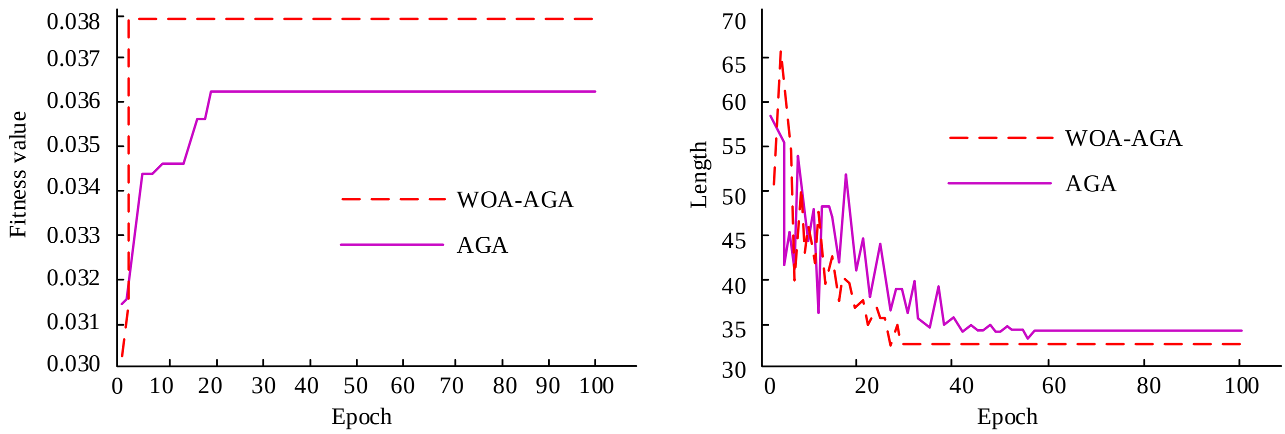
Figure 8 shows the change comparison results of the fitness curve and iteration curve of the two algorithms. In Figure 8(a), AGA completes the iteration around the 18th iteration, and the overall convergence rate improves. However, AGA-WOA reaches a more stable state in the third iteration, and its fitness value is higher. In Figure 8(b), the AGA-WOA algorithm can quickly find the direction of the target point in the early stage of the path optimization process, with a fast convergence speed.

To further verify the superiority of the WOA AGA algorithm, 15 simulation experiments are conducted using the WOA AGA and AGA models, and the corresponding results are obtained in Table 2. Data showes that the average AGA path value is 27.4300, and the average time is 18.2943. The average WOA-AGA path value is 27.3342, and the average time is 17.3683. The operational efficiency of WOA-AGA has increased by 3.87% compared to AGA. Therefore, the stability and accuracy of the



(a) AGA Algorithm Path Simulation (b) WOA-AGA Algorithm Path Simulation

Figure 7: Path Planning Results of WOA-AGA and AGA Algorithms



(a) Fitness curve (b) Iterative curve

Figure 8: Change Results of fitness Curve and Iteration Curve of AGA and WOA-AGA

WOA-AGA algorithm are superior to the AGA algorithm, verifying its effectiveness. The difference between the two algorithms is significant ($P < 0.05$), which further verifies the superiority of WOA-AGA model over AGA model.

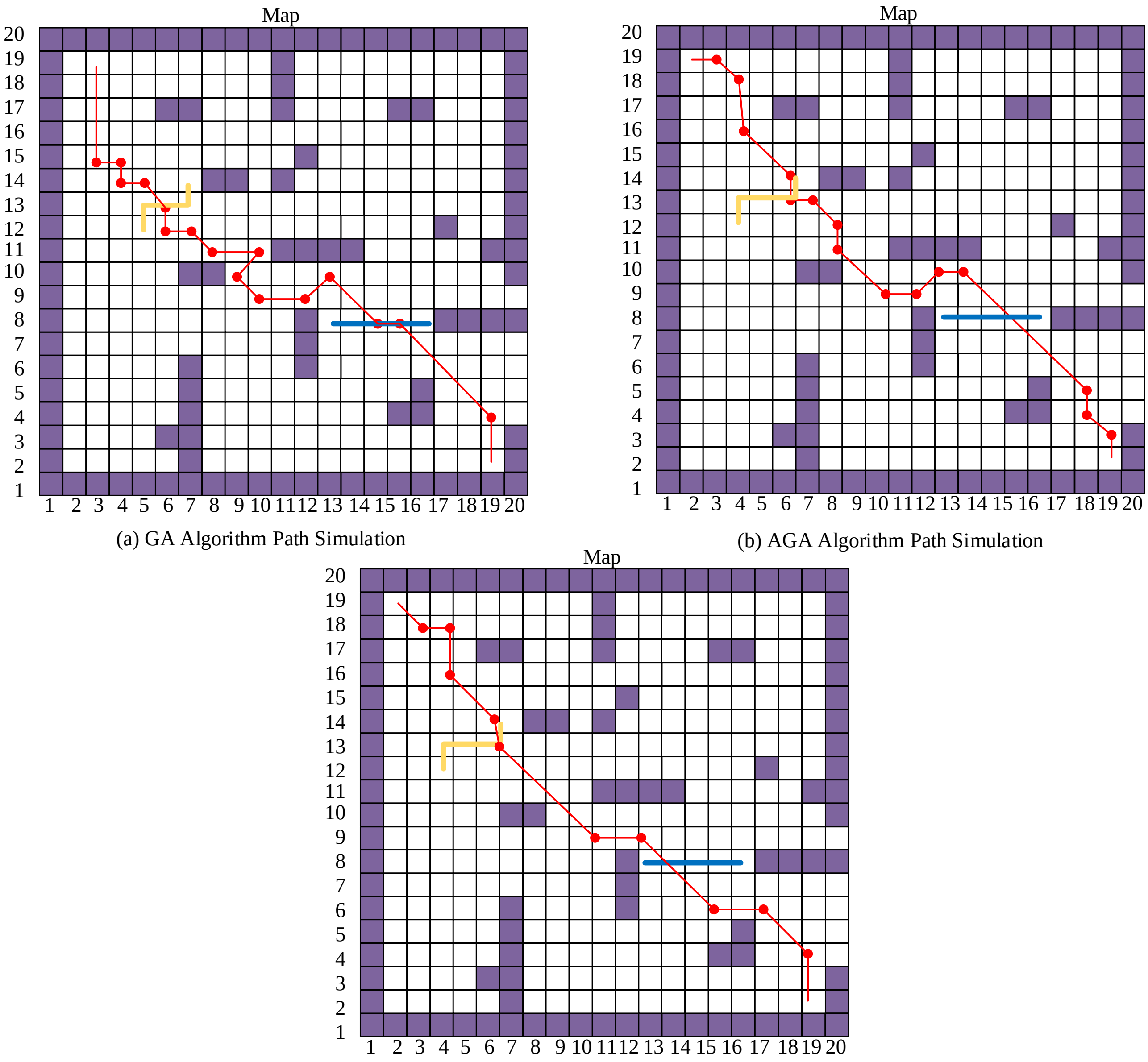
Table 2: Path length and time obtained from 15 simulations of WOA-AGA and AGA

Number of runs	AGA		WOA-AGA		P	
	Length	Time consuming	Length	Time consuming	Length	Time consuming
1	27.4123	18.3314	27.4101	17.5641	0.000	0.015
2	27.6547	18.3369	27.5163	17.6547	0.011	0.004
3	27.1234	18.2215	27.0025	17.2314	0.000	0.000
4	27.5689	18.2691	27.4411	17.3356	0.001	0.000
5	27.8745	18.3612	27.7796	17.5874	0.000	0.001
6	27.4789	18.3958	27.3326	17.1596	0.023	0.000
7	27.4587	18.2214	27.3369	17.2584	0.000	0.000
8	27.0125	18.2036	27.0001	17.3674	0.004	0.002
9	27.1546	18.2639	27.0458	17.5687	0.000	0.000

Table 2 continued from previous page

Number of runs	AGA		WOA-AGA		P	
	Length	Time consuming	Length	Time consuming	Length	Time consuming
10	27.3698	18.3514	27.2945	17.4926	0.004	0.001
11	27.5686	18.2845	27.4316	17.4763	0.011	0.002
12	27.3345	18.3364	27.2211	17.2358	0.000	0.000
13	27.2269	18.3758	27.2023	17.1475	0.000	0.000
14	27.3365	18.2369	27.2211	17.1236	0.016	0.011
15	27.8745	18.2245	27.7769	17.3218	0.000	0.000

4.2 Robot Path Simulation Analysis in Dynamic Environment



(a) GA Algorithm Path Simulation

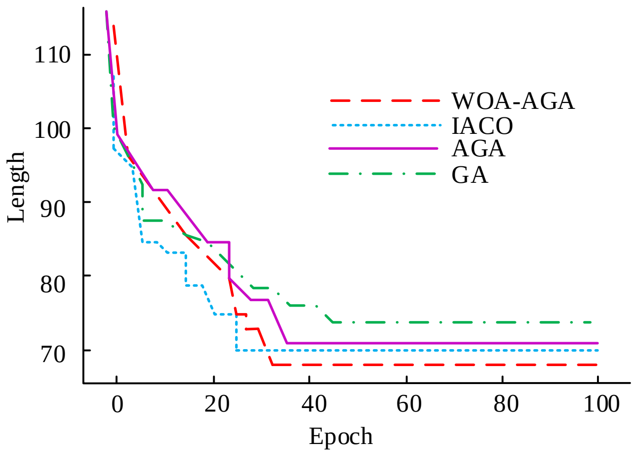
(b) AGA Algorithm Path Simulation

(c) WOA-AGA Algorithm Path Simulation

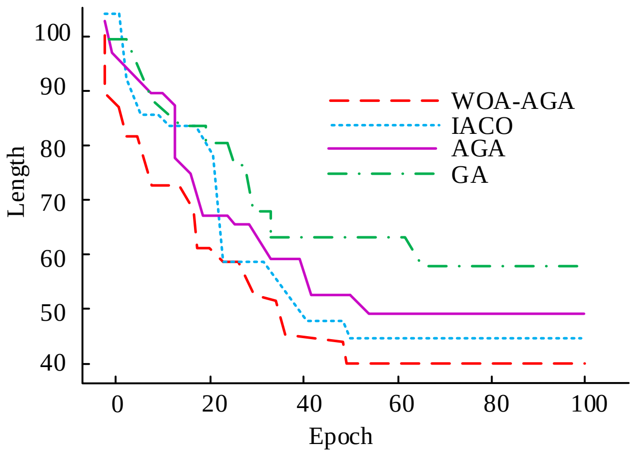
Figure 9: Path Planning for Three Methods in a Dynamic Environment

To test AGA-WOA's feasibility and superiority in path planning, an experimental comparison is conducted between the AGA-WOA hybrid algorithm and GA and AGA algorithms. To verify the superiority of AGA-WOA hybrid genetic algorithm under different paths, simulation verification will be conducted on two completely different paths in a dynamic environment. The 20×20 grid environment space used in the simulation experiment contains two dynamic obstacles, A and B, represented by yellow and blue identification lines. The paths planned by the three methods in a dynamic environment are shown in Figure 9. Among them, the path length of GA algorithm is 31.2547. The path length planned by AGA is 27.7856. The path length planned by WOA-AGA is 26.1236. As a result, the path obtained by WOA-AGA has shorter distances and better planning results. In addition, the GA algorithm completes its iteration in the 46th iteration. The AGA algorithm completes the 15th iteration. The WOA-AGA algorithm completes iteration 5. The above results also demonstrates the superior path planning performance of the WOA-AGA model.

Finally, the experiment selectes two more complex scenarios, namely "narrow valleys" and "mazes", for path planning. Experiments are conducted to compare and verify WOA-AGA with the currently popular Improved Ant Colony Optimization (IACO) algorithm. Figure 10 shows the planning results of four algorithms. In Figure 10(a), WOA-AGA requires approximately 33 iterations to find a feasible path, and the obtained path is shorter than the other three algorithms. WOA-AGA is approximately 8 cells shorter than GA, 4 cells shorter than AGA, and 2 cells shorter than IACO. In Figure 10(b), for a more complex "maze" map, even after 100 random population initialization, it is difficult for GA to find an optimal and feasible path. In the "maze" map, on average, the feasible path of WOA-AGA was about 18 cells shorter than GA, about 9 cells shorter than the path obtained by AGA, and about 5 cells shorter than IACO.



(a) Narrow valley map



(b) Maze map

Figure 10: Path Planning Results of Four Algorithms

5 Conclusions

In this study, a WOA-AGA model is proposed. The model introduces the difference degree function and WOA algorithm to optimize the local optimal solution of GA algorithm, long convergence time and unstable optimization results. The experiment is simulated under dynamic and static conditions. Under static environment, the results show that the average path and average time of 15 simulation experiments of GA algorithm are 27.8768 and 18.5491. The average path of AGA algorithm is 27.6643, and the average time is 18.4374. The efficiency of AGA is increased by 1.87% compared with GA, which verifies the effectiveness of AGA. AGA and WOA-AGA were simulated. AGA completes the iteration around the 18th iteration, and AGA-WOA reaches a more stable state with higher fitness value in the third iteration. The results of 15 simulation experiments of WOA-AGA show that the average path of AGA is 27.4300 and the average time is 18.2943. The average path of WOA-AGA algorithm is 27.3342, and the average time is 17.3683. The operating efficiency of WOA-AGA is improved by 3.87% compared with AGA, which verifies its effectiveness. Under dynamic environment, the experimental results of the three algorithms show that the path length of GA algorithm is 31.2547; The path length planned by AGA algorithm is 27.7856; The path length planned by WOA-AGA algorithm is 26.1236. The simulation results of two complex scenarios show that the feasible path of WOA-AGA is about 18 cells shorter than that of GA, 9 cells shorter than that of AGA, and 5 cells shorter than that of IACO. Therefore, WOA-AGA has superior performance and good application prospect. The limitation of this study is that path planning for more complex scenarios is not possible. In future research, the concepts of grid point continuity, insertion operator, and penalty function can be considered to explain the path planning of WOA-AGA mobile robot in more detail.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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