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Intelligent Object Avoidance Method Design of Railroad Inspection Robot Based on Particle Swarm Algorithm

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Abstract. In order to make the railroad inspection robot better adapt to its complex working environment, it is especially important to study the robot object avoidance algorithm. The WOA algorithm has simple and understandable structure and strong optimization ability but is prone to local convergence. IWOA-PSO is used for railway inspection robots. The performance of IWOA-PSO in the experimental results is better than that of WOA and PSO, and the average accuracy and standard deviation of the IWOA-PSO can better reach the theoretical optimal value in the function tests, and it has performance close to the theoretical value. In the simple environment object avoidance route planning, the minimum path length of IWOA-PSO is 850 mm, which is 53.6% less than that of the PSO algorithm, and the search time is 13.12 seconds, which is 5.11 seconds less than that of PSO algorithm; in the ordinary environment object avoidance route planning, the minimum path length of IWOA-PSO is 830 mm, while the path length of PSO algorithm is 1339 mm, the former is 38% less than the latter, and the search time of IWOA-PSO is 14.05 seconds less than PSO algorithm, so the method has better effect on object avoidance.

Keywords: object avoidance route planning, PSO, IWOA, railroad inspection

1 Introduction

At present, China's railway transportation is in a rapid and stable development stage, and railway substation and distribution station is an important foundation for railway development. With the continuous growth of railway mileage, the number of transformer and distribution stations is increasing, and the potential safety hazards are also rising, which directly threaten the safety of railway operation and passengers. Therefore, the railway patrol inspection plays an important preventive role in the overall safety. At present, the domestic inspection mode is mainly manual inspection, and there are many problems in the current infrastructure construction. In terms of personnel, with the continuous increase of railway mileage and infrastructure construction, the supply of personnel is gradually insufficient, and it is difficult for inspectors to thoroughly implement the inspection procedures in their work. In terms of data, the patrol record of manual patrol inspection is incomplete and cannot serve big data applications. In terms of fault detection, there is less data information collected manually and the coverage is not wide enough to eliminate potential faults. To some extent, the disadvantages of manual inspection cannot be avoided, so artificial intelligence provides a new way to solve such problems. Robot is the most representative product of the development of intelligence. The research to application of intelligent robots is also one of the standards to measure national science and technology innovation, and also the representative of high-end manufacturing level [1]. After a long period of development, China's intelligent robotics industry has been rapidly enhanced, and has rich experience in the development and production of robots, which can help people to complete many patrols, inspections and other works. Railroad inspection robots are typical representatives [2]. Although China is the world's largest consumer market for industrial robots, it is still a late starter in the research of intelligent robots, so there is a large gap between China's industrial robots and advanced countries in terms of structure, object avoidance route planning, precise control, and other key technologies [3]. The further development of intelligent robots has become a pointer for China's development toward an intelligent manufacturing powerhouse. In recent years, a variety of intelligent algorithms have been applied in the field of robotics to effectively improve the accuracy of robot kinematics solution. Robot object avoidance paths are accurately planned so that robots can adapt to more complex working environments [4]. Therefore, the main goal of the research is to

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realize the obstacle avoidance function, so as to achieve the function of railway inspection. The research adopts the combination of whale optimization algorithm and particle swarm optimization algorithm to design the intelligent obstacle avoidance function for the railway inspection robot, so that the robot can better complete the work during the inspection, so as to effectively guarantee the safety of the railway work.

The first part introduces the research status of particle swarm optimization and inspection robot. In the second part, the problem that particle swarm is easy to fall into local optimal solution is improved, and the improved algorithm is applied to robot patrol path planning. In the third part, the performance of the inspection robot is verified by simulation experiments. The fourth part summarizes the experimental results and analyzes the advantages and disadvantages of the methods used in the research.

2 Related Work

Particle swarm optimization algorithm has been widely studied at home and abroad. Che et al. [5] used the optimal Latin hypercube design to spatially sample the design variables of the impeller to achieve the overload free characteristics of the vertical long axis fire pump. After sampling, particle swarm optimization algorithm was used to optimize the design. The results showed that the optimized vertical long shaft fire pump had no overload characteristics in the range of 1.5q. Ding et al. [6] studied a particle swarm optimization algorithm based on migration learning, and introduced a particle update strategy with adaptive crossover and clustering guided mutation to enhance the search ability of the algorithm. The experimental results showed that the migration learning mechanism could speed up the search efficiency of particle swarm optimization algorithm and enabled the algorithm to obtain a better optimal path. Maghayreh et al. [7] studied an image encryption algorithm based on multi-objective particle swarm optimization algorithm, DNA coding sequence and one-dimensional logistic mapping. Simulation experiments and security analysis showed that the correlation coefficient and entropy of the ciphertext were very good, which could resist various typical attacks and had good encryption effect. Zhang et al. [8] proposed a new constraint processing technique based on differential distance measure for constrained multi-objective optimization problems. Comprehensive experiments on several benchmark problems showed that the algorithm was competitive with the most advanced constrained evolutionary multi-objective optimization algorithm. Zhang et al. [9] used particle swarm optimization algorithm to determine the optimal lighting design scheme to achieve the total energy consumption of the middle lighting. The results showed that the lighting scheme optimized by the proposed bilateral symmetric lighting parameter optimization algorithm saved 28.63% energy than the original design scheme using the on-site tunnel lighting method and lamp selection.

Gao et al. [10] used a wearable rehabilitation robot based on mobile communication network for electromyography control to improve the rehabilitation effect of the robot after stimulation and used biofeedback as well as fuzzy control rules for rehabilitation of patients to prevent muscle atrophy in patients with disabilities caused by accidents or diseases. Mishra et al. [11] designed a robot part for environmental actions which generates control signals as well as electrical components of the environment and issues commands to the robot through computer programming to make the robot challenge different difficulties in technology and analyze the importance of intelligent robot manufacturing. Zheng et al. [12] proposed a fuzzy sliding mode control method which can obtain accurate dynamics model in practical application, so that KUKA robot system can accomplish more accurate and complex task commands, while is safer with interference function to the outside. Chen et al. [13] made new methods for human-robot interaction by combining two channels, 3D gesture interaction and natural language command, to help the robot and human to achieve efficient interaction, thus making the robot serve people more fully. Tran et al. [14] proposed an integrated controller for self-driving vehicles, which can properly control the robot when there is a sudden obstacle on the road. The controller is able to respond appropriately to emergency situations when sudden obstacles appear on the road. The results showed that the controller is very good in preventing instability and collisions. Tian et al. [15] proposed a new object avoidance algorithm, which optimizes the feasible motion of closed-loop control system and dynamic repulsion field by introducing parameter decision-making power. Through the analysis of experimental results, under this algorithm, the robot can not only successfully complete the tracking task, but also successfully avoid various obstacles. He et al. [16] studied the tracking task of intelligent mobile robot with target avoidance, applied the predictive control method of linear model in the model of nonlinear robot, and proposed different structure development strategies. Experiments showed that the control method reduces the computational task of Newton method by half, which proves the effectiveness of the algorithm. Li et al. [2] proposed a hybrid control method of robot to avoid robot collision, and improved the motion planning algorithm by introducing the method of deep reinforcement learning. After characteristic training, task completion and object avoidance can be achieved at the same time in the operation space, which verified the feasibility of this method in target avoidance.

To sum up, the research of scholars on PSO has been relatively mature. PSO can enhance the search ability of the model and optimize the model solution, but the algorithm is prone to fall into the problem of local optimal solution. In the field of robot obstacle avoidance, the robot has realized object detection and automatic path planning, but there is still room for improvement in path planning. Therefore, the research combines IWOA algorithm with PSO algorithm to obtain a new robot obstacle avoidance algorithm. Compared with the above algorithm, this algorithm can avoid the local optimal solution, and further improve the model performance, so as to ensure the safety and stability of the robot in the inspection process.

3 Intelligent Object Avoidance Model of Railroad Inspection Robot Based on IWOA-PSO

3.1 PSO Hybrid Swarm Intelligence Algorithm Incorporating Improved Whale Optimization

The particle swarm algorithm starts with the bird swarm behavior optimization problem. The particle refers to each optimization problem corresponding to a feasible solution, each particle adaptation value is determined by an optimization function. The particle moves according to a certain speed to change its own distribution in the search space so as to seek the best location in the Worldwide, and the motion of the particles shares experience [17-19]. Assume D is the search space exists m particles, the velocity of the i-th particle will be vector $V = [v_{i1}, v_{i2}, ..., v_{iD}]$, the location of the particle will be vector $X = [x_{i1}, x_{i2}, ..., x_{iD}]$, the first-best value of the particle itself will be vector $p_{best} = [\ p_{i1}, p_{i2}, ..., p_{iD}]$, the global optimal particle population of the whole particle will be vector $g_{best} = [g_{i1}, g_{i2}, ..., g_{iD}]$. The update formula of particle velocity and position is shown in Equation (1).

$$\begin{cases} v_{ij}(t+1) = v_{ij}(t) + c_1 r_1 (p_{ij}(t) - x_{ij}(t)) + c_2 r_2 (p_{gj}(t) - x_{ij}(t)) \\ x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \end{cases} . \tag{1}$$

In Eq. (1), r_1 and r_2 indicate random numbers with uniform distribution that are obeyed in the range of [0, 1]. c_1 and c_2 denote learning factors, which are constants, and t denotes the number of iterations. As shown in Eq. (1), the particle velocity update formula consists of three parts, $v_{ij}(t)$ denotes the inertial part, $c_1r_1(p_{ij}(t)-x_{ij}(t))$ denotes the self-awareness part, and $c_2r_2(p_{gj}(t)-x_{ij}(t))$ denotes the social-awareness part. The social-awareness part describes the collaboration and sharing of group history experience information among particles, which indicates that the particles have the tendency to move with group history position seeking. The particle flight speed is the particle search step size. A step size that is too large will bring the algorithm to be divergent and difficult to converge; a step size that is too small will reduce the ability of the algorithm to search globally [20, 21]. Therefore, inertia weights need to be introduced to balance the advantages and disadvantages. The velocity and position update formulas for adding inertia weights are shown in Eq. (2).

$$\begin{cases} v_{ij}^{t+1} = wv_{ij}^{t} + c_1 r_1 (p_{ij}^{t} - x_{ij}^{t+1}) + c_2 r_2 (p_{gj}^{t} - x_{ij}^{t}) \\ x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \end{cases} . \tag{2}$$

The inertia weight is represented in Eq. (2). Through the linear decreasing strategy of inertia weight, when the inertia weight is reduced, it can ensure that particles focus on exploration in the early stage of algorithm search, that is, local optimization of the algorithm, and focus on development in the late stage of algorithm iteration, that is, global optimization of the algorithm. The calculation formula of w is shown in Equation (3).

$$w = w_{\max} - \frac{(w_{\max} - w_{\min})t}{t_{\max}} . \tag{3}$$

In Eq. (3), $w_{\max}$ and $w_{\min}$ represents the extreme value of inertia weight, and $t_{\max}$ represents the maximum iteration. Usually, the maximum value of inertia weights is 0.9 and the minimum value is 0.4. The particle swarm algorithm incorporating inertia weights is called the standard PSO algorithm. The particle population size is generally set to 20 to 50. The number of particles is related to the search range, the larger the number the longer the algorithm running time. The larger the inertia weight, the stronger the individual particle search ability. The maximum speed of the particles is taken as $[-v_{max}, v_{max}]$, the search time of the algorithm can be adjusted by the speed. The maximum number of iterations is the stopping condition of the algorithm. The convergence and global optimization performance of particle swarm optimization algorithm can be improved by improved whela optimization algorithm (IWOA). The Whela Optimization Algorothom (WOA) is a new intelligent sequential minimal optimization inspired by the group hunting style of humpback whales. The algorithm divides its hunting into three processes: encirclement of prey, bubble net attack, and prey search. Assuming that the current optimal individual location is the optimal solution location, the rest of the optimization individuals will update the location according to the current optimal location. The specific expression of position update is shown in Eq. (4).

$$\begin{cases} \vec{X}(t+1)+\vec{A}\cdot\vec{D}=\overrightarrow{X^*}(t) \\ \vec{D}=\left|\vec{C}\cdot\overrightarrow{X^*}-\vec{X}(t)\right| \\ \vec{A}=\vec{a}*\vec{C}-\vec{a} \\ \vec{C}=2*\vec{r_2} \\ \vec{a}=2-\dfrac{2t}{MaxIter} \end{cases}. \tag{4}$$

In Eq. (4), $\vec{D}$ denotes the current individual whale and the optimal position spacing, t denotes the current iterations, $\overrightarrow{X^*}$ denotes the current optimal solution location obtained, $\vec{A}$ and $\vec{C}$ denote the coefficient vectors, $\vec{r_1}$ and $\vec{r_2}$ denote the random numbers in the interval [0,1]. $\vec{a}$ decreases linearly from 2 to 0 during the iteration, and *MaxIter* represents the maximum number of iterations. The bubble net attack predation mode is a humpback whale shrinking the envelope while spiral bubble predation. The mathematical model of this spiral predation behavior is shown in Eq. (5).

$$\begin{cases} \vec{X}(t+1)=\dfrac{\cos(2\pi l)}{\left(\left|\overrightarrow{X^*}-\vec{X}(t)\right|\cdot e^{bl}\right)^{-1}}+\overrightarrow{X^*}(t) \\ \overrightarrow{D'}=\left|\overrightarrow{X^*}-\vec{X}(t)\right| \end{cases}. \tag{5}$$

In Eq. (5), $\overrightarrow{D'}$ represents the distance between the target prey and the search particle, b is the shape parameter of the pair of spirals, and l is a random number in the range of [0,1]. In order to simulate this simultaneous behavior, the probability of occurrence of each of the two behaviors is set to 50%, and the mathematical model is Eq. (6).

$$\vec{X}(t+1)=\begin{cases} \overrightarrow{X^*}(t)-\vec{A}\cdot\vec{D},\ p\in(-\infty,0.5) \\ \dfrac{\cos(2\pi l)}{(\overrightarrow{D'}\cdot e^{bl})^{-1}}+\overrightarrow{X^*}(t),\ p\in[0.5,+\infty) \end{cases}. \tag{6}$$

In Eq. (6), P is a random number between 0 and 1. When $\left|\vec{A}\right|\geq 1$, it indicates that the whale is currently making a random swim for food in the global space, which corresponds to a wide survey range, and its mathematical model is as in Eq. (7).

$$\begin{cases} \vec{D}=\left|\vec{C}\cdot\overrightarrow{X(t+1)}+\vec{A}\cdot\vec{D}-\vec{X}\right| \\ \overrightarrow{X(t+1)}+\vec{A}\cdot\vec{D}=\overrightarrow{X_{rand}} \end{cases}. \tag{7}$$

In Eq. (7), $\overrightarrow{X_{rand}}$ indicates the position direction of randomly selected individuals in the current scale, i.e., it is used to represent a random whale, and $\overrightarrow{X(t+1)}$ denotes the position of the current whale individual in the first generation. The WOA algorithm has the advantages of setting fewer parameters, faster convergence, and easy execution of the model, but it also has obvious disadvantages, such as the tendency to converge early and fall into local optimality. Therefore, it is necessary to enhance the global search capability and the search accuracy of the WOA algorithm. The introduction of chaotic mapping to initialize the population can accelerate the convergence speed of the algorithm, and its mathematical model is shown in Eq. (8).

$$z_{k+1} = \left\{ \begin{matrix} 2z_k, z_k \in [0, 0.5] \\ 2 - 2z_k, z_k \in [0.5, 1] \end{matrix} \right\} \quad k \in \{0,1,2\} \ . \tag{8}$$

In Eq. (8), k denotes the number of mappings and z_k denotes the value of the k mapping function. The chaotic sequence is obtained by using chaotic mapping so that the initial solution can be distributed in the solution space as uniformly as possible. In addition, the global search capability of the algorithm is enhanced by introducing adaptive weights and adaptive thresholds to avoid falling into local optima and improve the search accuracy. The improved whale position formula as well as the adaptive weight and adaptive threshold change formula are shown in Eqs. (9), (10) and (11).

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{wX^*}(t) - \vec{A} \cdot \vec{D}, p < p' \\ \dfrac{\cos(2\pi l)}{(\vec{D}' \cdot e^{bl})^{-1}} + \overrightarrow{wX^*}(t),\ p \geq p' \end{cases} . \tag{9}$$

$$w(t) = e^{-(\frac{t}{\max\_iter})^k} \ . \tag{10}$$

$$p' = 1 - \log_{10}(1 + \frac{9t}{\max\_iter}) \ . \tag{11}$$

In Eqs. (9), (10) and (11), t denotes the iteration, max_*iter* represents the maximum value of the iteration k is coefficient, which is randomly taken within [0,1] and follows a uniform distribution, and p' denotes the self-use probability threshold. The hybrid swarm intelligence algorithm, i.e., hybrid whale particle swarm algorithm, is obtained by fusing the particle swarm algorithm and the improved whale optimization algorithm. Fig. 1 shows the specific process of IWOA-PSO.

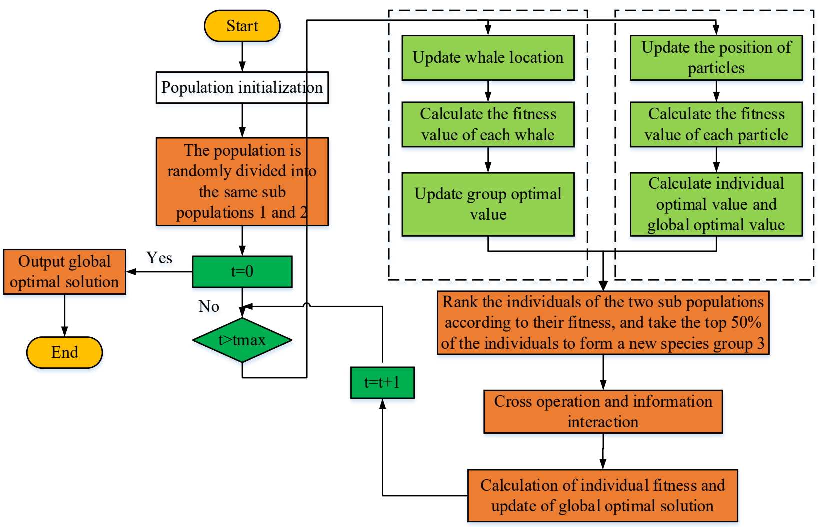


Fig. 1. IWOA-PSO flow chart

As shown in Fig. 1, the IWOA-PSO randomly divides the population into two subpopulations 1 and 2, where subpopulation 1 applies the IWOA algorithm and subpopulation 2 applies the PSO algorithm to find the best. When the two subpopulations are updated, the fitness values of the individuals in the two subpopulations are compared, and the top 50% of the best individuals in the two subpopulations are ranked and recombined into a new population 3, and then the information interaction between the individuals in the new population is realized according to the crossover principle to add new individuals to the algorithm population. The principle of crossover is shown in Fig. 2.

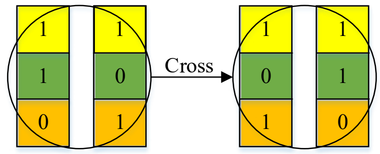


Fig. 2. Crossover principle

Fig. 2 shows the crossover operation between individuals, specifically the operation of partially exchanging the codes of the two individuals to be optimized to generate new individuals. Finally, the population with individual recombination is randomly returned to the sub population before recombination through the previously selected comparison column to update the individual of the population.

3.2 IWOA-PSO-based Object Avoidance Route Planning for Inspection Robots

Inspection robots need to work safely and efficiently when moving in mission space, and it is important to find a collision-free motion method that allows the robot to intelligently avoid obstacles as well as people. It is also important to reduce mechanical vibrations and motion shocks during object avoidance to improve the robot's working life and smooth operation [22-24]. The research establishes the coordinate axis as shown in Fig. 3 through the inspection robot manipulator as the coordinate system, and Li Tong polynomial trajectory solves it to complete the robot object avoidance design.

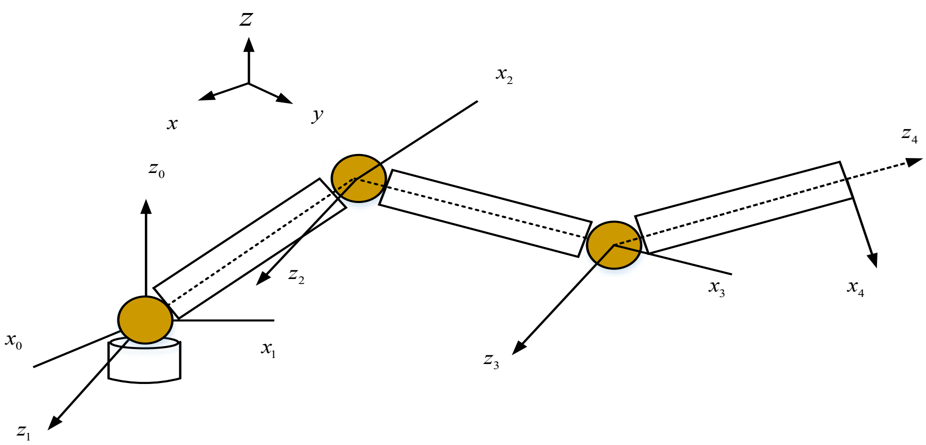


Fig. 3. Establishment of coordinate system for solving path equations

Planning of the robot and robot joints in the motion space. The third polynomial trajectory planning is suitable for the case where the velocity at the start and end points are zero, and the expression is given in Eq. (12).

$$\begin{cases} \theta(t) = a_0 + t(a_1 + a_2 t + a_3 t^2) \\ \dot{\theta}(t) = a_1 + t(2a_2 + 3a_3 t) \\ \ddot{\theta}(t) = 2(a_2 + 3a_3 t) \end{cases} . \quad \textbf{(12)}$$

In Eq. (12), $\theta(t)$, $\dot{\theta}(t)$ and $\ddot{\theta}(t)$ represent the angle of motion, angular velocity and angular acceleration, respectively, and a_1, a_2 and a_3 represent the coefficients, respectively. For special applications that require more accurate trajectory and less vibration, higher Lagrange polynomial interpolation is required for trajectory planning. The general expression for the fifth order polynomial interpolation is given in Eq. (13).

$$\begin{cases} \theta(t) = a_0 + t(a_1 + a_2 t + a_3 t^2 + a_4 t^3 + a_5 t^4) \\ \dot{\theta}(t) = a_1 + t(2a_2 + 3a_3 t + 4a_4 t^2 + 5a_5 t^3) \\ \ddot{\theta}(t) = 2a_2 + 2t(3a_3 + 6a_4 t + 10a_5 t^2) \end{cases} . \quad \textbf{(13)}$$

Eq. (13) makes the robot motion curve smoother by increasing the interpolation polynomial order, but the computation of the high-order polynomial interpolation function is very complicated when solving the robot trajectory curve, and considering the advantages of B spline curve with derivative continuity, scalability and local adjustability, the B spline is taken to construct the path. The K-sample curve is used to construct the robot trajectory, and its expression is shown in Eq. (14).

$$P(u) = \sum_{i=0}^{n} Q_i N_{i,k}(u) . \quad \textbf{(14)}$$

In Eq. (14), Q_i is the control fixed point of the curve, i denotes the serial number of the control vertex of the B spline curve, and $N_{i,k}(u)$ is the k-th (k+1 th order) B spline basis function. During robot motion, it is also necessary to avoid excessive mechanical vibrations. Although the stability of the robot can be improved by reducing the jitter, the limitation makes the whole running time of the robot significantly longer and affects the efficiency. Therefore, Best route setting is considered and optimized in terms of the coupled and contradictory motion performance indicators of runtime and impact (i.e., acceleration). This not only ensures the work efficiency, but also ensures the smoothness of the robot in motion and reduces the impact. The optimization equation is given in Eq. (15).

$$\begin{cases} \min f = K_T N \sum_{i=1}^{n-1} t_i + a_1 \cdot \sum V_c + a_2 \cdot \sum A_c + a_3 \cdot \sum J_c + \partial K_J \sum_{j=1}^{N} \sqrt{\dfrac{\int_0^T ((\dddot{q}_j(t)))^2 dt /}{T}} \\ subject\ to \begin{cases} |\dot{q}_j(t)| \le V_{jm} \\ |\ddot{q}_j(t)| \le A_{jm} \\ |\dddot{q}_j(t)| \le J_{jm} \end{cases} \end{cases} . \quad \textbf{(15)}$$

In Eq. (15), N represents the number of robot joints, t_i represents the time interval between path points, n represents the number of path points, $\dot{q}_j$ represents the jth joint speed, $\ddot{q}_j$ represents the jth joint acceleration, $\dddot{q}_j$ represents the jth joint acceleration, V_{jm} represents the jth joint velocity constraint, A_{jm} represents the jth joint acceleration constraint, J_{jm} represents the jth joint acceleration constraint, and K_J represents the time weighting coefficient, K_T represents acceleration weighting coefficient, and T represents motion time. Considering the difference between the running time of the robot and the square of the impact in the order of magnitude, the elasticity coefficient ∂ is added to the Eq. (15) to balance the order of magnitude of the motion time and the impact. K_J and K_T are the weighting factors, which must meet the requirements of $K_T + K_J = 1$. By adjusting the sizes of K_J and K_T, the total running time and acceleration can be optimized to some extent.

4 Utility Analysis of Object Avoidance Path for Inspection Robot Based on IWOA-PSO

4.1 IWOA-PSO Performance Test Results Analysis

To validate the performance of IWOA-PSO proposed by the study, the experiments take the remaining multiple related algorithms for comparative analysis, which includes IWOA algorithm, WOA algorithm, GWO algorithm, PSO algorithm, MPA algorithm, and HHO algorithm. Different algorithms are substituted into a variety of test functions to solve, and the performance of the algorithm is analyzed by comparison. Using the idea of control variable method, the parameters of the algorithm are set to the same state. The initial population parameter of the algorithm is 30, the parameter of the model iteration is 500, and the model ends training when the parameter value is reached. The curve convergence of each algorithm in the test function is obtained through simulation experiments, as shown in Fig. 4.

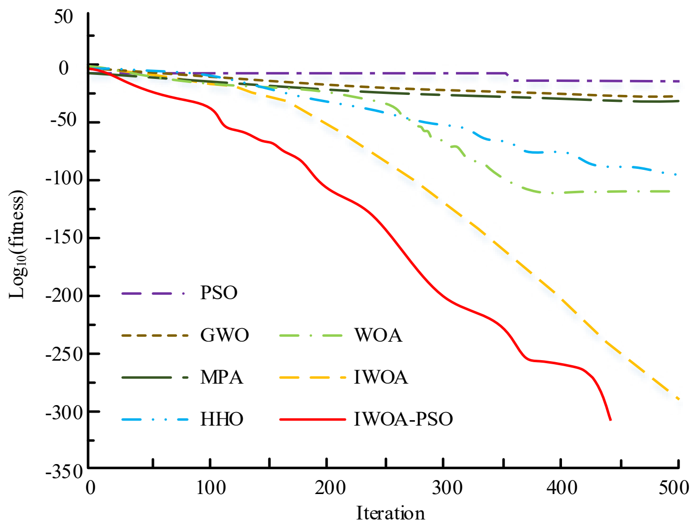


Fig. 4. Comparison diagram of curve convergence of each algorithm in unimodal test function

The comparison graph of convergence curves in Fig. 4 reveals that the performance of each of the seven algorithms is different, among which the IWOA-PSO proposed in the study converges faster in the single-peak test function, and the optimal solution of the function is completed when the iteration reaches 450 times, and the remaining algorithm will not be terminated until other models reach the set maximum iteration. Meanwhile, the lower value of Log value represents the higher accuracy in finding the optimal solution. IWOA-PSO also has the best performance in accuracy with a Log value of -320, so the algorithm plays the best performance in the function. The performance comparison results in the multiple peak function are shown specifically in Fig. 5.

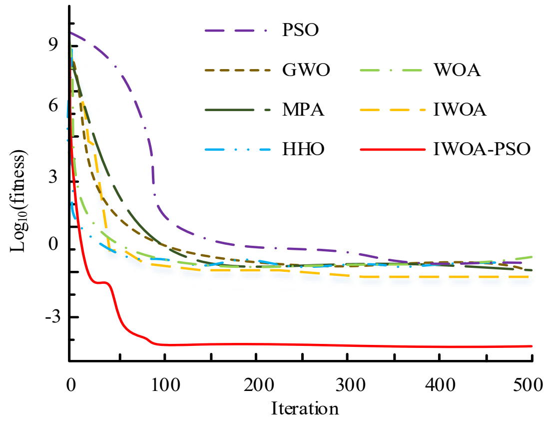


Fig. 5. Comparison diagram of curve convergence of each algorithm in multimodal test function

The convergence curve trend of each algorithm is observed from the result graph of multi peak test function, where the IWOA-PSO proposed in the study has faster convergence rate and convergence performance compared with other algorithms. The IWOA-PSO is the first to show the inflection point in training, which indicates that the algorithm can go beyond the local optimum to find the optimal solution. Because the IWOA-PSO introduces an adaptive threshold to balance the local search of the population as well as the global search capability. Only this algorithm converges to the optimal solution with the curve satisfying high precision for a number of iterations up to 100. The remaining six algorithms all perform well in terms of convergence speed, but are far inferior to the IWOA-PSO in terms of precision. The Log value of the precision of the remaining algorithms is basically around 0, and the Log value of the precision of the IWOA-PSO is around -4. The final performance results of each function in the fixed multi-peak function are shown in Fig. 6.

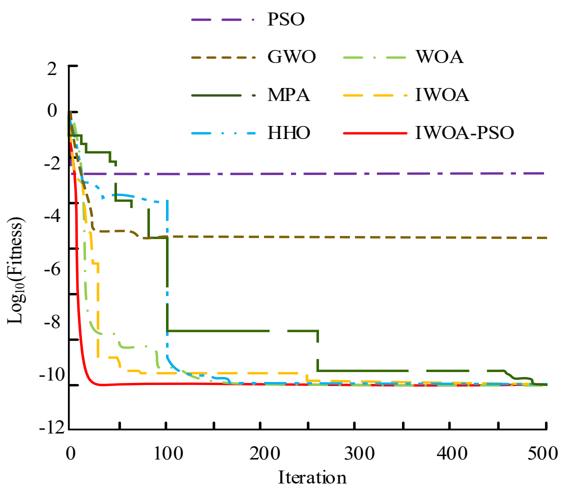
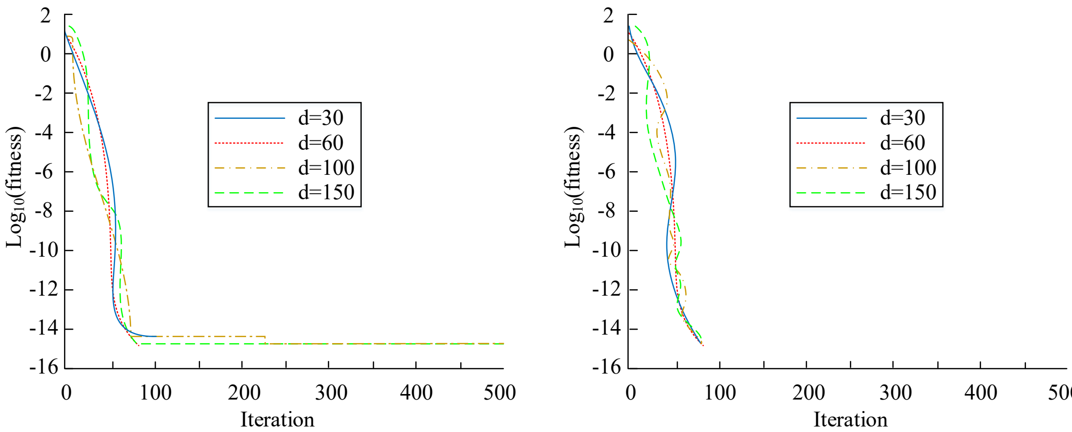


Fig. 6. Comparison diagram of curve convergence of each algorithm in fixed multimodal test function

From the convergence curve of the fixed multi-peak function in Fig. 6, it can be learned that five of the seven algorithms have small differences in accuracy in this test function, and the Log values are all around -10. Analyze from the function convergence rate, IWOA-PSO has the fastest performance in this aspect. It can be seen from the fixed multimodal function convergence curve in Fig. 6 that five of the seven algorithms have little difference in the accuracy of the test function, and the Log value is about - 10. In the benchmark tests of single peak test function, multi peak test function and fixed multi peak test function, IWOA-PSO algorithm has good performance. From the perspective of applicability, the algorithm meets various types of benchmark tests, which shows that the algorithm has strong applicability; From the performance point of view, the algorithm converges at the earliest time in the benchmark test and has strong stability, which shows that the budgetary estimate method has the characteristics of fast convergence and strong optimization ability.

After confirming the high performance of the research algorithm, the performance of the algorithm was tested for different function dimensions. The population size and the number of iterations of the IWOA-PSO were kept constant, and the dimension of the function was set to 30, 60, 100 and 150 with four different parameters. The average adaptation value of the algorithm was tested using typical test functions F10 and F11, and the test results are shown in Fig. 7.



(a) Performance test in algorithm F10 test function

(b) Performance test in algorithm F11 test function

Fig. 7. Performance test results of IWOA-PSO under different function dimensions

From the average adaptation value convergence curves in Fig. 7, it is known that the IWOA-PSO has high percent of accuracy in functions of different dimensions, and the function convergence rate of the algorithm in the test function is basically unaffected by the increasing dimensionality of the function, which indicates that the ability of the algorithm to find the global optimal solution is not affected by external conditions, high-dimensional and nonlinear optimization problems.

4.2 Analysis of Object Avoidance Results Based on IWOA-PSO

To verify the superiority of IWOA-PSO in object avoidance route planning, two obstacles are set in the robot workspace and simulation experiments are performed in Matlab using PSO, WOA and IWOA-PSOs. In the simulation, the robot motion start angle is [0°, 0°, 0°, 0°, 0°, 0°, 0°], the end motion angle is [120°, -40°, 30°, 80°, 70°, 50°], the robot end-effector start point is set to (390, 0, -175), the end point is set to (-134, 233, -362), and the simple environment with few to many obstacles and the general environment for robot object avoidance route planning. The object avoidance route planning in the simple environment is shown in Fig. 8.

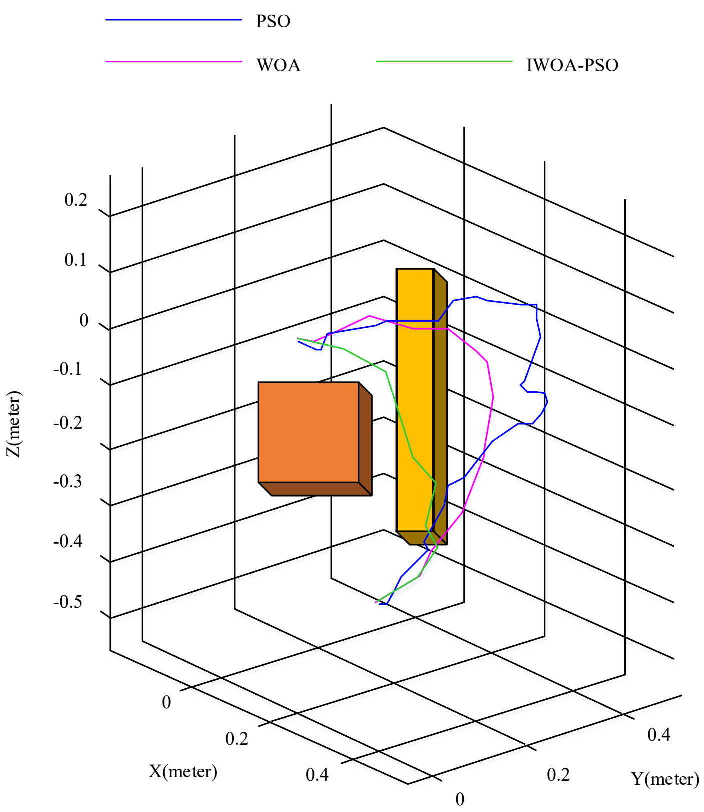


Fig. 8. Object avoidance route planning in simple environment

From Fig. 8, the PSO has the farthest object avoidance planning path and the most tortuous path, the WOA algorithm is second, while the IWOA-PSO has the shortest object avoidance path and a smoother path, so it has the best quality of the object avoidance path. In order to quantitatively analyze the quality of object avoidance paths of the three algorithms, Table 1 shows the search time and path length size of each of the three algorithms.

Table 1. Route planning results of three algorithms in simple environment

Algorithm	Search time (s)	Path length (mm)
PSO	18.23	1832
WOA	17.07	1007
IWOA-PSO	13.12	850

From Table 1, IWOA-PSO has the smallest object avoidance path length of 850 mm, WOA algorithm has the longest object avoidance path length of 1007 mm, and PSO algorithm has an object avoidance path length of 1832 mm. Therefore, IWOA-PSO has a better path than PSO algorithm and WOA algorithm paths by 53.6% and 15.6% respectively. And the search time of IWOA-PSO is 13.12 seconds, which is 3.95 seconds less than WOA algorithm and 5.11 seconds less than PSO algorithm. In the experiment, the inspection robot based on IWOA-PSO algorithm can find the best inspection path in the path planning, which shows that the algorithm has stronger optimization ability. The object avoidance paths of the three algorithms in a common environment are shown in Fig. 9.

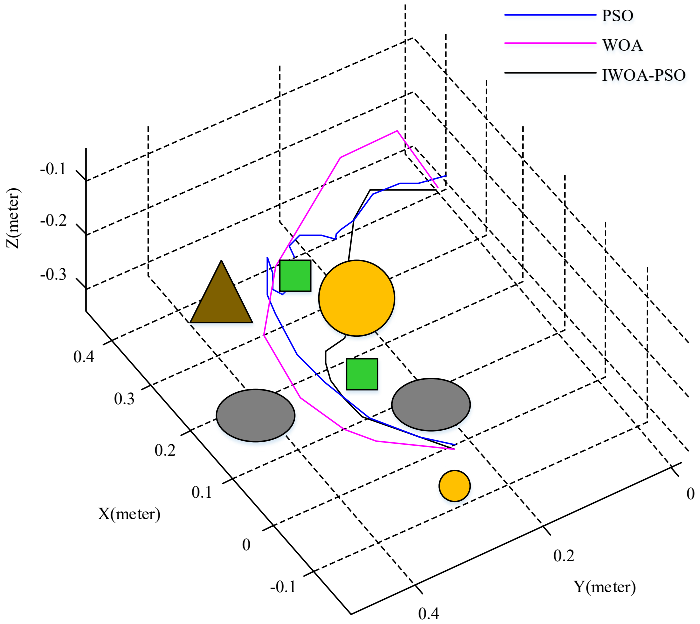


Fig. 9. Object avoidance path of three algorithms in ordinary environment

From Fig. 9, it can be intuitively seen that the object avoidance path obtained by using IWOA-PSO is the shortest and the path curvature is the lowest and smoothest, while the PSO algorithm gets the longest object avoidance planning path and the WOA algorithm gets the most curvy and least smooth object avoidance planning path curve. The advantages and disadvantages of the three algorithms can be quantitatively analyzed from Table 2.

Table 2. Route planning results of three algorithms in ordinary environment

Algorithm	Search time (s)	Path length (mm)
PSO	38.29	1339
WOA	45.23	1009
IWOA-PSO	24.24	830

As can be seen from Table 2, the minimum object avoidance path length obtained by IWOA-PSO is 830 mm, the second longest object avoidance path length obtained by WOA algorithm is 1009 mm, and the longest object avoidance path length obtained by PSO algorithm is 1339 mm, so IWOA-PSO reduces the path cost by 17.7% and 38% than WOA algorithm and PSO algorithm, respectively. It has better route planning effect. Analyze from the aspect of search time, the IWOA-PSO has the lowest search time of 24.24 s, the WOA algorithm has the longest search time of 45.23 s, and the PSO algorithm has the second longest search time of 38.29 s. Therefore, the IWOA-PSO reduces 46.41% and 36.69% of the time than the two algorithms, respectively. In the experiment, IWOA-PSO algorithm shortens the path search time of the inspection robot, reduces the path planning mileage, and makes the inspection robot have higher work efficiency.

5 Conclusion

Railroad inspection robots often encounter obstacles of different sizes and shapes in their work. In order to complete inspection tasks safely, stably and efficiently, it is crucial to study the object avoidance path of railroad inspection robots. The algorithm performance comparison shows that the IWOA-PSO obtains the highest average accuracy as well as the smallest standard deviation in the single-peak test function, and theoretically, the optimal solution of the algorithm is 0, while the WOA algorithm and PSO algorithm cannot obtain the theoretical optimal value. In the performance test of multimodal test function, the average accuracy of IWOA-PSO is 0, 8.88E-16 and 0, while the corresponding average accuracy of PSO algorithm is 4.67E+01, 2.76E-01 and 9.21E-03. Therefore, IWOA-PSO has higher accuracy and better global optimal solution than PSO. Simulation of object avoidance in simple environment, the object avoidance path lengths and search times obtained by IWOA-PSO, WOA algorithm and PSO algorithm are 850 mm, 1007 mm and 1832 mm and 13.12 seconds, 17.17 seconds and 18.23 seconds, respectively, from which it can be seen that IWOA-PSO saves 53.6% of path cost than PSO algorithm and 5.11% than PSO algorithm saves 5.11 seconds of search time. In the simulation of object avoidance in general environment, IWOA-PSO also obtained the minimum object avoidance path of 830 mm, which is 17.7% and 38% less than WOA algorithm and PSO algorithm, and the search time is 24.24 seconds, which is 46.41% and 36.69% less than WOA algorithm and PSO algorithm. Therefore, the effectiveness of the algorithm for the inspection robot object avoidance application is verified. The research improves WOA algorithm by introducing weight, and proposes IWOA algorithm by combining it with PSO algorithm, which is applied to global path planning. The simulation results show that the path planned by the algorithm has the advantages of short distance and less time consumption. However, there are still some deficiencies in the research. The obstacles used in the research are mostly regular objects, while in reality, obstacles are often irregular objects. Therefore, the subsequent research needs to be verified with the real environment as the experimental conditions.

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