

Research on Ship Path Planning Based on Improved Whale Optimization Algorithm

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Abstract. In view of the problems of the traditional Whale Optimization Algorithm (WOA) when dealing with ship path planning tasks, such as easy to fall into local optimum and weak later search ability, an improved Whale Optimization Algorithm (IWOA) was proposed. Firstly, the algorithm introduces Tent chaotic map to initialize the population, enrich the diversity of the population, and enhance the global search ability. Secondly, the stochastic differentiation algorithm is introduced to update the individual position through the cross-mutation operation, retain the optimal solution, and improve the convergence speed and robustness. Then, the Levy flight strategy is introduced, which combines random step size and stagnation disturbance mechanism to balance long-distance and short-distance search and avoid local optimum. Finally, combined with the fused ship motion constraints (path smoothness, maximum steering angle, safety margin), etc., the ship path planning is carried out in the rasterized nautical chart. Simulation experiments show that the improved whale optimization algorithm improves 6% and 34% in terms of path length and running time compared with the traditional whale optimization algorithm, which can better meet the needs of ships in complex navigation environment.

Keywords: Ship path planning, Whale optimization algorithm, Ship Motion Constraints, Levy flight strategy, Random Differential Evolution.

1. Introduction

With the growing trend of economic globalization, the industry has put forward a high level of functionality and efficiency of ships in the new era. As a core tool for future maritime transportation, the planning quality of intelligent ships' navigation paths directly affects shipping costs, cargo delivery timeliness, energy consumption, and navigation safety. Path planning refers to the intelligent body under certain constraints (e.g., shortest time, shortest path length) to find an optimal path from the starting point to the end point from the complex environment under the premise of avoiding obstacles. The global path planning algorithms that are widely used on ships include: A* algorithm, Dijkstra's algorithm, Rapidly-exploring Random Tree (RRT), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA) and so on.

The above algorithms are effective in specific scenarios, but they generally have the disadvantages of high computational complexity, poor adaptability to the environment as well as easy to fall into local optimization. Zhai et al^[1] proposed an improved sparse A* algorithm, which takes into account the ship's initial position and heading, the safety range and so on, but does not take into account the other dynamic factors. Zhu et al^[2] proposed an improved Dijkstra's algorithm which reduces the redundant points of path planning by using mathematical models, thus reducing the cost, but its adaptability to the environment is poor. Liu et al^[3] introduced a ship route planning method based on the adaptive step Informed-RRT* algorithm, which reduces the slow convergence and redundant sampling characteristics of RRT. Intelligent population algorithm realizes the planning of complex paths by comparing and updating the optimal solution, and its algorithm is highly accurate and efficient, which can effectively reduce the complexity in ship route planning, and has attracted extensive attention from scholars at home and abroad. Luan et al^[4] proposed a new hybrid genetic algorithm, which provides a dynamic mutation rate to the mutation operator of the ordinary genetic algorithm and a switchable global-local search method that The premature convergence and high time-consuming adaptation computation of the genetic algorithm were

reduced. Deng et al^[5] used particle swarm optimization (PSO) and BP neural network to fit the relationship between trajectory curvature, desired speed and optimal gain parameters for the controller to achieve path planning and trajectory tracking prediction.

Whale Optimization Algorithm (WOA) is a new type of intelligent population algorithm proposed by Australian scholar Mirjalili in 2016, the principle comes from the humpback whale's "bubble net feeding strategy", compared with other algorithms, the algorithm has a strong global search and fewer algorithmic parameters, and has been widely used in the fields of machine learning, path planning. It is widely used in machine learning, path planning, and data prediction design. However, due to the problem of the search mechanism of the traditional WOA itself, the WOA is easy to fall into the local optimal solution situation, and thus can not find the global optimal solution; at the same time, in the late iteration of the random search strategy triggering rate is relatively low, and it is difficult to explore the new region, which will reduce the ability of the global search. Hu et al^[6] improved the population initialization strategy and introduced the random multi-dimensional movement strategy and adjusted the parameters, to enhance the ability to jump out of the local optimal. Wu et al^[7] improve the Whale Optimization Algorithm (WOA) through the hierarchy of Gray Wolf Algorithm (GWO) and apply the improved algorithm to UAVs to verify its performance. Zhao et al^[8] combine PSO with WOA and introduce nonlinear inertial weight factors into the standard PSO and WOA algorithms to improve the global search ability and convergence speed, but need to adjust the parameters of the two algorithms.

According to the above mentioned deficiencies, this paper proposes an Improvement Whale Optimization Algorithm (IWOA), firstly, Tent chaotic mapping^[9] is introduced to initialize the population, and its inclusion can maintain the diversity of the population to enhance the global search ability; secondly, Levy flight strategy^[10], its alternating long and short distance search method, and combined with the stagnation perturbation strategy to better enhance the performance of the whale optimization algorithm; finally, the stochastic differential algorithm^{[11][12]} is added for optimization, by applying the stochastic differential strategy to update the position again after an individual updates its position, and retaining the best-performing position, the method can significantly prevent the population from being restricted to the local optimum. It is also combined with ship-related characteristics such as path smoothness, ship steering constraints, safety margins and maximum steering angle, and improved by multiple strategies, aiming to improve the performance of the algorithm, and verified in simulation experiments.

2. Introduction to the Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) is an intelligent population optimization algorithm that simulates the humpback whale bubble net feeding behavior. The algorithm consists of the following three main steps: encircling prey phase, bubble net feeding phase, and stochastic exploration phase.

2.1 Encircling The Prey Phase

The humpback whale discovers the prey and gradually approaches the prey, which in WOA is equivalent to the search agent gradually moving towards the currently known optimal solution and updating its own position according to the optimal solution to round up the prey, a process denoted as:

$$\vec{X}(t+1) = \vec{X}'(t) - \vec{A} \cdot \vec{D} \quad (1)$$

$$\vec{D} = \left| \vec{C} \cdot \vec{X}'(t) - \vec{X}(t) \right| \quad (2)$$

where t is the number of iterations, A , C are the coefficient vectors; $X(t+1)$ is the updated position of the other individuals; X' is the position vector where the optimal solution is currently obtained, and will be updated if a new optimal solution is obtained.

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (4)$$

$$\vec{a} = 2 - \frac{2t}{t_{\max}} \quad (5)$$

where a is the convergence factor, which is linearly reduced from 2 to 0 during the iteration process, and r_1, r_2 are random values between $[0,1]$. A is reduced by the reduction of a to achieve a reduced enclosure of the position. Fig. 1 illustrates the different positions to reach the next position of the whale, i.e., to reach the current optimal solution surrounding, by adjusting A, C when solving a two-dimensional problem.

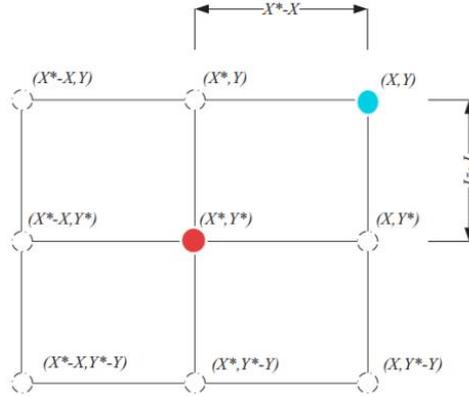


Fig. 1 The next possible location of the whale

2.2 Bubble Net Predation Phase

This phase simulates the process of fine search and exploitation by whales in the vicinity of the optimal solution, gradually narrowing down and concentrating on the most probable areas as the whales approach their prey in a spiral pattern that mimics the behavior of a humpback whale creating a bubble net. The process is:

$$\vec{X}(t+1) = \vec{D}^* \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}'(t) \quad (6)$$

$$\vec{D}^* = \left| \vec{X}'(t) - \vec{X}(t) \right| \quad (7)$$

where D represents the distance between the i th whale $X(t)$ and the prey, b is a parameter that defines the shape of the spiral, and l is a random number between $[-1,1]$ that denotes element-by-element multiplication, i.e., when l is 1, the whale moves to the side farthest from the prey, and when l is -1, the whale moves to the side closest to the prey.

The whale is circling and approaching the prey in a constricted-surround mechanism and a spiral model, and both have a 50% probability p_n can select either the constricted-surround mechanism or the spiral model to update the whale's position, being able to toggle between spiral or circular movements. The position update formula:

$$\vec{X}(t+1) = \begin{cases} \vec{X}'(t) - \vec{A} \cdot \vec{D} & p_n < 0.5 \\ \vec{D}^* \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}'(t) & p_n \geq 0.5 \end{cases} \quad (8)$$

2.3 Stochastic Exploration Phase

During the whales' prey roundup phase, whales also randomly search for prey based on each other's location, which allows whales to randomly jump out of the current search area and explore globally. This prevents the entire population from prematurely aggregating near a local optimal solution. This process is:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_r - \vec{X} \right| \quad (9)$$

$$\vec{X}(t+1) = \vec{X}_r - \vec{A} \cdot \vec{D} \quad (10)$$

X_r is the position of the randomly exploring whale. When $|A| < 1$, the whale moves towards the currently known optimal solution; when $|A| > 1$, the whale explores randomly away from the current target solution.

3. Introduction to the Whale Optimization Algorithm

3.1 Tent Chaos Mapping

In practical applications, WOA usually adopts random data as the initial position of the population, although the populations are all distributed in the search space, it may make the population distribution uneven or relatively single, the performance of the algorithm can not be further realized, and the effect of searching for the optimal is not ideal. Chaotic mapping has the characteristics of randomness and high efficiency, which can enrich the diversity of populations, make the WOA optimization better, and enhance its global search ability. Ma et al ^[13] proposed that Tent chaotic mapping has better traversal and high efficiency. Therefore, in this paper, Tent chaotic mapping is chosen to initialize the population sequence, while considering the population boundary vector, stagnation processing and re-initialization. When the optimal solution has no improvement for 5 consecutive generations, re-initialization is triggered. The Tent chaotic sequence mapping process is:

$$H_{n+1,k} = \begin{cases} \varepsilon H_{n,k} & H_{n,k} < 0.5 \\ \varepsilon(1 - H_{n,k}) & H_{n,k} \geq 0.5 \end{cases} \quad (11)$$

Where n is the current number of iterations, k is the number of whales, and ε is a random number between $[0,2]$, in this paper ε is taken as 2, which can make the population distribution more uniform and improve the coverage of the initial population.

3.2 Random Differential Evolution

The stochastic differential algorithm evaluates the new position of the population through the operation of crossover and mutation, and the optimal solution is obtained through evaluation and updating, which improves the algorithm's ability to search locally and enhances the search speed of WOA. In the stochastic differential strategy, adding random elements to the stochastic differential algorithm while utilizing crossover and mutation allows individuals to update and retain the optimal solution after performing the stochastic differential algorithm to increase the diversity of the population. The process is as follows:

$$G(t+1) = \alpha(G_{best}(t) - G(t)) - \varphi(G'(t) - G(t)) \quad (12)$$

$$\vec{V} = \vec{G}_a + F \cdot (\vec{G}_b - \vec{G}_c) \quad (13)$$

$$U_j = \begin{cases} V_j & \text{if } rand_j < CR \\ G_{ij} & \text{otherwise} \end{cases} \quad (14)$$

Where α , φ are random numbers between $[0,1]$, $G'(t)$ is a random individual whale. v, U represent the crossover and mutation operations respectively, F is the scaling factor and CR is the crossover probability. After these two steps new fitness values are updated, and if a new globally optimal solution is found, the leader position is updated.

3.3 Levy Flight Strategy

The Levy flight strategy usually uses alternating long and short distance searches, while its step lengths and directions are chosen randomly, and the step lengths and directions obey specific probability distributions (Levy distributions), which means that a single iteration may jump to a

very long distance. The Levy distribution has a long tail, characterized by relatively short step lengths for most of the steps, but occasionally very long step lengths occur, forming so-called “jumps”. When searching with the Levy flight strategy, the whale population is widely distributed in space and has a strong global search capability, and its stochastic and “jumping” characteristics can help the WOA to jump out of the local optimal solution and better explore the global search space. The formula for the Levy flight strategy is as follows:

$$LevyPDF(x) = \frac{1}{x\sqrt{2\pi}} e^{-\frac{1}{2x}} \quad (15)$$

$$\sigma_u = \left[\frac{\Gamma(1+\beta) \sin(\pi\beta/2)}{\beta\Gamma((1+\beta)/2) 2^{(\beta-1)/2}} \right]^{\frac{1}{\beta}} \quad (16)$$

$$\begin{cases} u \sim N(0, \sigma_u^2) \\ v \sim N(0, \sigma_v^2) \end{cases} \quad (17)$$

$$Levy(\beta) \sim \frac{\sigma_u \times u}{|v|^{\frac{1}{\beta}}} \quad (18)$$

where LevyPDF(x) is used to describe the distribution of steps in the Levy flight; Γ is the gamma function, β is a random value between [0,2] for the shape parameter of the step distribution, which is usually taken as 1.5; and σ_v is 1.

Levy flight strategy to get the latest solution $X(t+1)$, is based on $X(t)$ combined with Levy step coefficients and random numbers to get a new solution, $G(t)$ represents the solution of the t -th generation, and $G(t+1)$ represents the new solution of the $(t+1)$ -th generation. ω is the step coefficient of which is given by the following formula:

$$G(t+1) = G(t) + \omega \oplus Levy(\beta) \quad (19)$$

3.4 Algorithmic Process

The flow of Improved Whale Optimization Algorithm (IWOA) is described as follows:

(1) Initialize the parameters of the algorithm, including population size, number of iterations, spatial dimensions and stagnation detection parameters;

(2) Initialize the location of search agents using Tent chaotic mapping to ensure diversity in the initial population and perform boundary checking;

(3) Calculate the fitness value of each search agent, update the global optimal solution, determine the pilot whale, and if the optimal solution is not improved for several consecutive iterations, trigger the stagnation processing mechanism, including partial individual reinitialization and random perturbation, to jump out of the local optimum;

(4) Update coefficients A, C, a, etc. according to Eqs. (3) ~ (5);

(5) Randomized Differential Algorithm (RDE) generates new individuals by performing crossover and mutation operations according to Eqs. (12)~Eqs. (14), and if a new fitness value, $G(t+1)$, is obtained, then the individual position is updated, which further improves the global search capability;

(6) Select some individuals to generate random steps according to the Levy distribution, combine the alternating long and short distance search, and calculate Levy steps according to Eqs. (16)~Eqs. (18) to avoid falling into the local optimum;

(7) When $P_n < 0.5$, then the location information is updated according to Eq. (1) and Eq. (2); when $P_n \geq 0.5$, when $|A| \geq 1$, then Eq. (12) and Eq. (19) are used to update the individual's location and compute the fitness; when $|A| < 1$, then the location is updated according to Eq. (6) and Eq. (7);

(8) Reach the maximum number of iterations, the loop stops and outputs the optimal solution G ; otherwise, return to the loop to execute steps (4)~steps (7).

The flowchart of the algorithm is as follows:

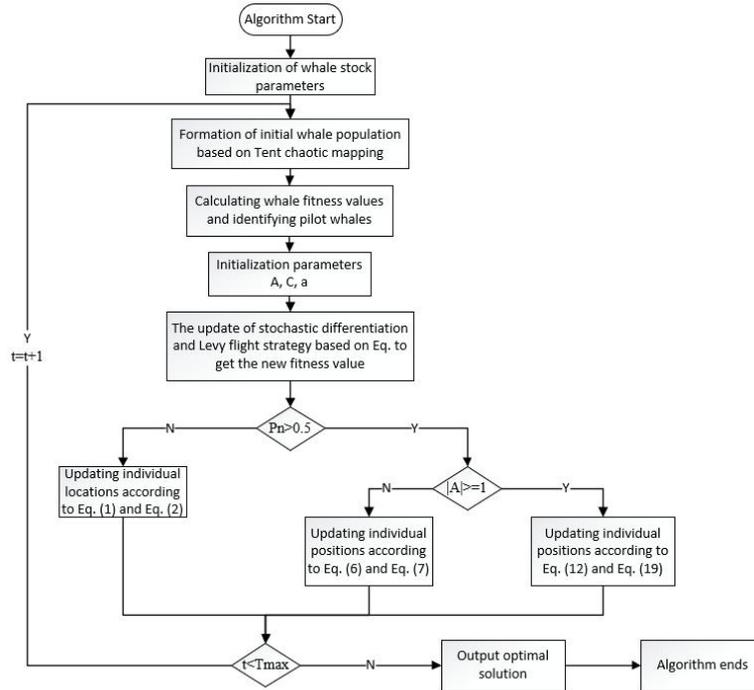


Fig. 2 Flowchart of Improved Whale Optimization Algorithm (IWOA)

4. Test Results And Analysis

4.1 Analysis Of Test Function Experiment Results

In this paper, two test functions F5 and F8 functions are selected in the CEC test set to test the performance of the algorithm before and after the improvement, and the performance of the algorithm is tested by solving the convergence curve of the optimal value of the function and the running time. The number of iterations of the algorithm is 500 times, the number of populations is set to 30, and the running results are shown in Fig. 3 to Fig. 6:

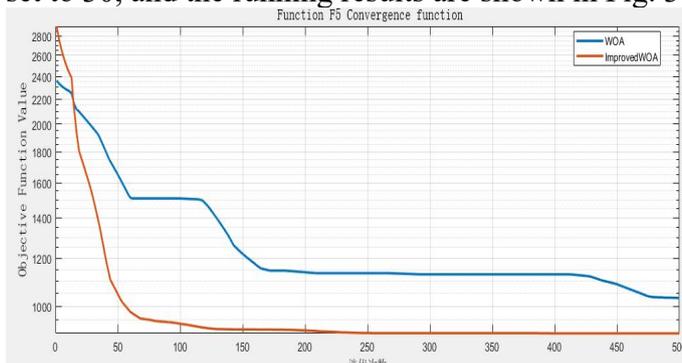


Fig. 3 F5 Algorithm convergence curve

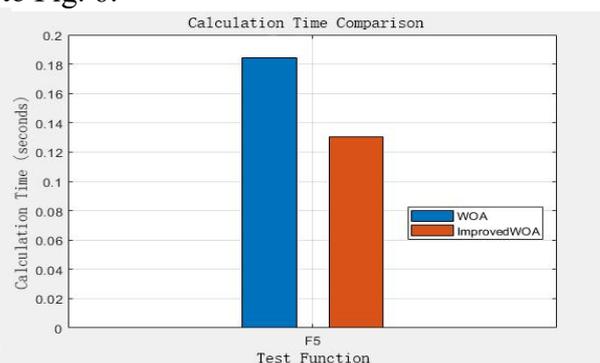


Fig. 4 F5 Algorithm running time

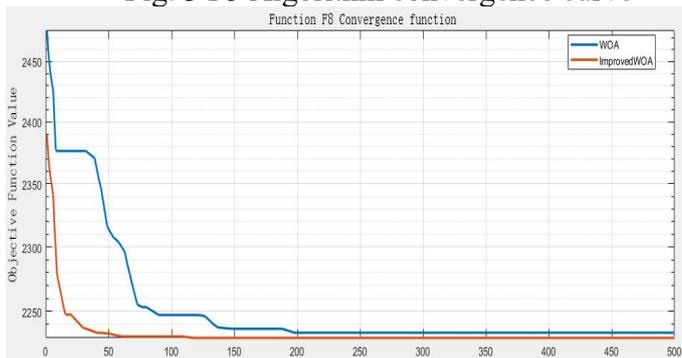


Fig. 5 F8 Algorithm convergence curve

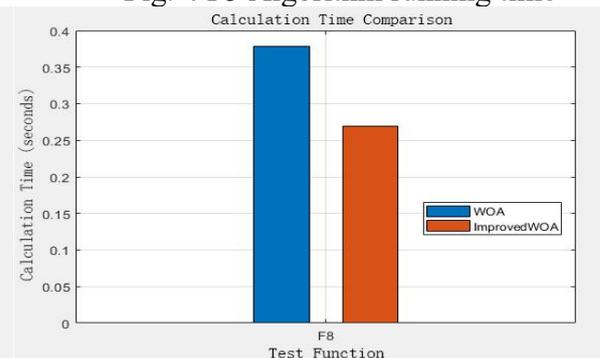


Fig. 6 F8 Algorithm running time

From the above pictures, it can be seen that the improved whale optimization algorithm has a stronger performance than the traditional whale optimization algorithm in terms of the optimal value of the convergence curve and the computation time, with a high accuracy of optimization, and IWOA can rapidly reduce the value of the objective function during optimization to reach a state closer to the optimal solution; in contrast, WOA converges slower and requires more iterations to get closer to the optimal solution, and this accelerated convergence property is particularly important for the This accelerated convergence is especially important for large-scale optimization problems; meanwhile, IWOA has stronger robustness and less performance fluctuation when encountering high-dimensional or complex problems, so that more stable results can be obtained.

4.2 Ship Path Planning Simulation Experiment

To verify the superiority of the improved IWOA algorithm in the real sea area, the length of the simulated ship is 30 meters, the safety distance is 50 meters, the draft is 4 meters, and the maximum steering angle does not exceed 30 degrees. Two domestic sea areas are also selected for rasterization, and the algorithms before and after improvement are applied to perform path planning on the rasterized maps, and their performance is examined. The rasterized nautical chart considers the water depth to ensure the safety and normal operation of the ship. The rasterized charts are shown in Fig. 7 and Fig. 8.



Fig. 7 Raster map of sea area 1



Fig. 8 Raster map of sea area 2

Both algorithms in the simulation experiments set the initial population size to 20, the maximum number of iterations to 200, the search space to $[-20,20]$, and the fitness function to consider the path weights, smoothness, turning radius constraints, maximum steering angle and straightness weights. The direction of the path is also limited in the generation path stage, i.e., do not appear the phenomenon of folding back, loopback, etc., and improve the straightness as much as possible in the obstacle-free area, so that the ship plans a shorter area to ensure the superiority of the path. Finally, the length of the path generated by the algorithm and the adaptation value are compared, and then the two algorithms are evaluated. The path planning graphs and adaptation convergence curve graphs obtained from the simulation experiments are shown in Fig. 9 to Fig. 12, respectively; the running time and path length are shown in Table 1.

Table 1. Simulation Experiment Results

	Algorithm	Path Length/n mile	Running Time/s
Sea Area 1	WOA	573.14	11.4963
	IWOA	534.69	7.2368
Sea Area 2	WOA	680.45	12.7652
	IWOA	638.27	8.9441

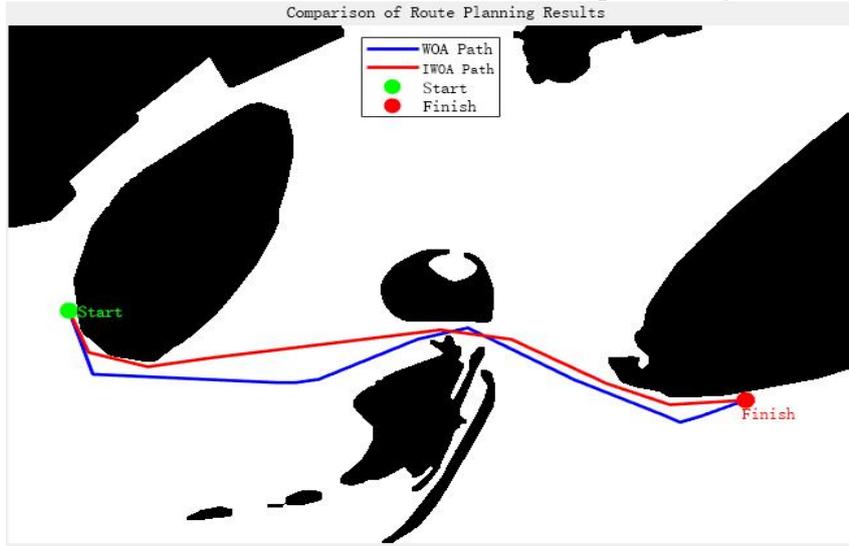


Fig. 9 Sea Area 1 Path Planning Diagram

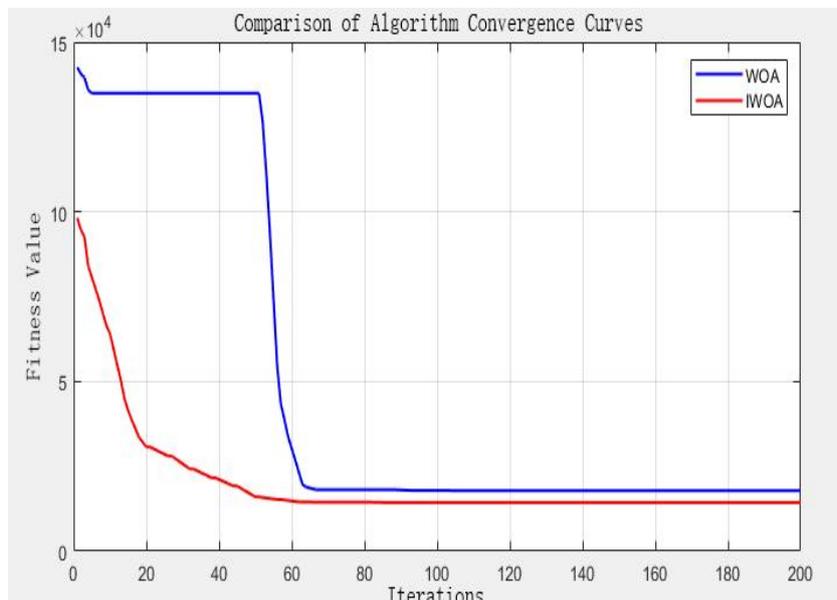


Fig. 10 Change curve of adaptation function for sea area 1

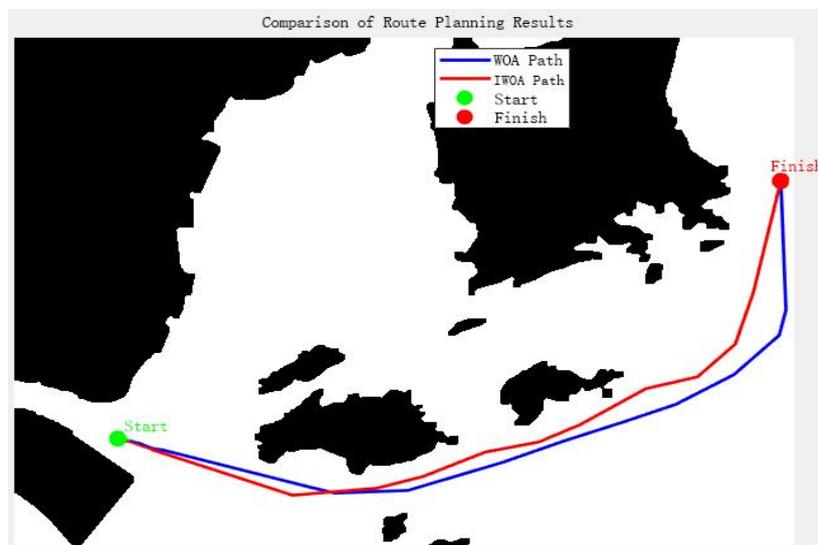


Fig. 11 Sea Area 2 Path Planning Diagram

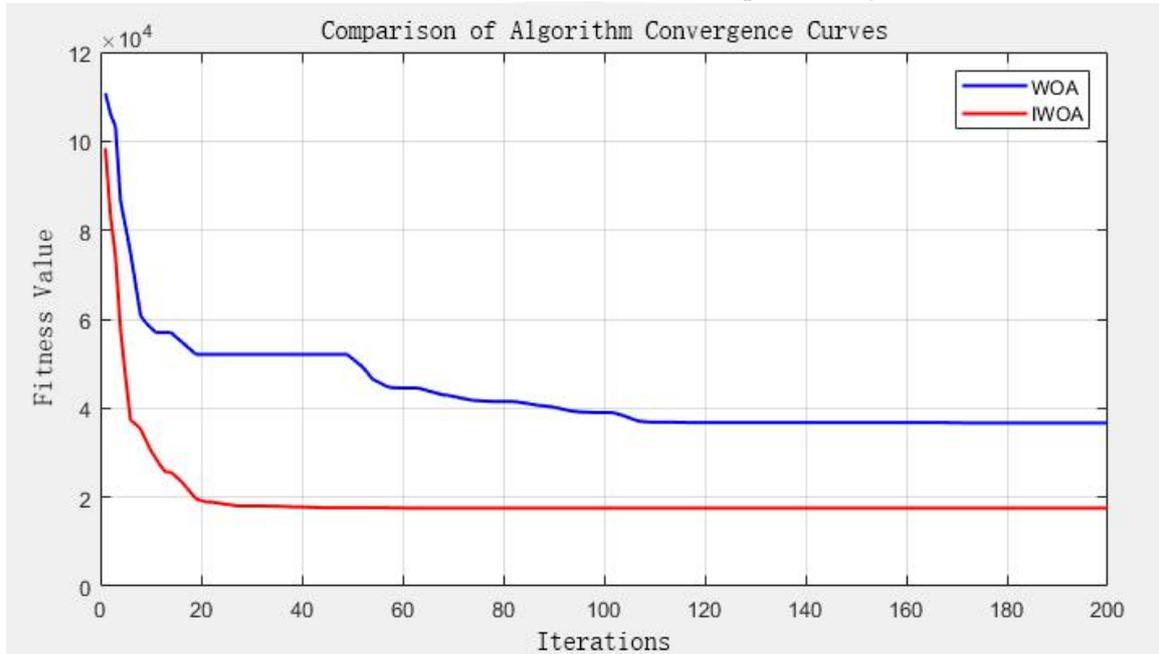


Fig. 12 Change curve of adaptation function for sea area 2

From Table 1 and the above images, it can be seen that compared with the traditional WOA algorithm, the IWOA algorithm shortens the path length by 6.71% and the running time by 37.1% on sea area 1, and shortens the path length by 6.20% and the running time by 29.9% on sea area 2. In summary, IWOA initializes the population by introducing Tent chaotic mapping, and the generated sequences are uniformly distributed in the solution space and have traversal, which can effectively improve the quality of the initial population and enhance the global search capability of the algorithm; it adopts stochastic differential algorithms and evaluates the location of new solutions through crossover and mutation operations, which avoids the algorithm from falling into the local optimum, and enhances search efficiency and robustness, and at the same time, for the At the same time, for the complex marine environment, variable constraints and objective functions faced by the ship, the parameters of the stochastic differential algorithm can be better adapted to the complex search space by adjusting the parameters of the stochastic differential algorithm to improve the versatility of the algorithm; the use of the Levy flight strategy combined with the randomized step size can effectively circumvent the situation of the local optimum, increase the search range and diversity of the individual whale, and provide a more realistic solution for the ship's path planning.

5. Conclusion

In this paper, an improved whale optimization algorithm is proposed for the ship path planning problem, which can plan the optimal route path from the starting point to the target point with high practicability and safety by considering the length of the ship, the safety distance and the draught situation at the same time. By testing in the standard function test set, it shows that the algorithm has good optimization ability and high efficiency; further path simulation experiments on the rasterized charts, compared with the original WOA algorithm, the IWOA algorithm reduces the length of the path by about 6%, and reduces the running time by about 34%. It is verified that the IWOA algorithm can plan the path for the ship in a better and safer way, and more dynamic factors should be added in the future research direction (e.g., considering the influence of other ships on the path planning of this ship), to further improve the ability of solving the practical problems.

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