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Unmanned Underwater Vehicles 3D Path Planning Utilizing the IGWO Algorithm

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ABSTRACT

Path planning is a crucial problem for unmanned underwater vehicles (UUVs) to accomplish their missions. To address the issues of slow convergence and limited search capacity in complex 3D environments, this paper introduces an Improved Grey Wolf Optimization (IGWO) algorithm. By integrating Particle Swarm Optimization (PSO) and an elite opposition-based learning strategy (EOBL), the IGWO algorithm enhances the Grey Wolf Optimization (GWO) method's update mechanism. This improvement bolsters global search capabilities while preserving GWO's local search strengths, increases convergence speed, and enhances robustness. To assess IGWO's effectiveness, 23 benchmark functions are used, confirming its superior performance. Finally, IGWO is applied to UUV path planning, with simulations across varied environments demonstrating its advantages over other algorithms.

1. Introduction

In recent years, the growing popularity of ocean exploration has spurred significant interest in underwater unmanned vehicle (UUV) research [1].Advances in science and technology have expanded UUV applications across both military and civilian sectors. [2]. In the civilian domain, UUVs are valued for their mobility and reliability and are commonly used for tasks such as marine water quality monitoring, bioprospecting, ocean data collection [3], seabed mapping, pipeline inspection, hull examination, marine debris collection [4], and passive vessel detection [5], etc. In military operations, UUVs offer high stealth capabilities, making them suitable for intelligence gathering, precision strikes, localization, and mapping. [2], etc. In particular, UUVs can perform some dangerous tasks, such as eliminating mines [6], fighting behind enemy lines and self-destruction. Due to the application of UUVs in various industries, the UUV problem involves multiple research fields, such as intelligent control algorithms[7-8], study on dynamic behavior [9], underwater environment exploration, path planning [10-11], trajectory tracking [12-13], multi-UUV formation control [14], task assignment, and navigation [15] and positioning [16].

In UUV path planning research, the primary challenge lies in navigating complex environments, where the UUV must avoid various static and dynamic obstacles to find an efficient route from the starting point to the destination. Path planning for UUVs can be categorized into global and local approaches. In global path planning, complete environmental information, including obstacles, is known beforehand, allowing for the design of an optimal path. Conversely, local path planning is applied in uncertain marine environments where full obstacle information is unavailable or where obstacles are moving. Additionally, UUV path planning must account for obstacle avoidance, path length, complex underwater conditions, and energy consumption.

With the development of UUV technology, a variety of solutions have emerged for the UUV path planning problem. For global path planning, it can be divided into traditional optimization algorithms and bionic intelligent optimization algorithms. Traditional optimization algorithms include: A star algorithm [17], Dynamic A star algorithm [18],the Dijkstra algorithm [19], and RRT algorithm [20], etc. Although the traditional algorithms have significant effects in dealing with 2D path planning problems, the search time increases exponentially with the increase of search depth when applied to 3D path planning. Bionic intelligent algorithms include particle swarm optimization algorithm (PSO) [21], genetic optimization algorithm (GA) [22], whale optimization algorithm (WOA) [23], ant colony optimization algorithm (ACO) [24], artificial bee colony optimization algorithm (ABC) [25] and grey wolf optimization algorithm (GWO) [26], etc. Bionic algorithms can exhibit local optimum problems and poor stability when dealing with path

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planning problems. For example, if there is unknown environmental information or moving obstacles in the global path planning, then local path planning is needed. For example, the Dynamic Window Approach (DWA) [27] is the more commonly used method. In addition, artificial intelligence methods such as reinforcement learning [28], deep learning [29], neural networks and deep reinforcement learning [30-31] are also applied to deal with local path planning problems. In recent years, many scholars have also used a hybrid of two or more algorithms to apply to the path planning problem. For example, [32] investigated the hybrid of whale optimization algorithm and cuckoo search algorithm to reduce the search time of AUV and reduce the energy consumption. [21] proposed an improved particle swarm optimization algorithm to solve the multi-objective global path planning problem. [33] came up with an improved moth flame optimization algorithm to help with path planning.

The literature discussed above has offered significant insights and ideas for UUV path planning. However, due to the vast amount of data in diverse, especially 3D, environments and the need for complex evaluation functions and constraints to identify feasible paths, a hybrid approach involving multiple algorithms proves effective. A hybrid algorithm can overcome the limitations of a single algorithm's performance and enhance overall stability.

The core steps and main contributions of this paper are as follows.

First, implementing an elite opposition-based learning strategy increases algorithm diversity and further boosts its global search and convergence speed. Next, combining the GWO and PSO algorithms enhances the ability to escape local optima and accelerates convergence. The improved GWO algorithm strengthens robustness, making it effective for UUV path planning in obstacle avoidance.

2. Related Works

2.1 Grey wolf algorithm

The grey wolf optimization (GWO) algorithm, introduced by Seyedali Mirjalili in 2014, is a nature-inspired metaheuristic based on the social hierarchy and hunting behavior of grey wolves. This hierarchy is represented by four types of wolves: alpha, beta, delta, and omega. The hunting strategy of grey wolves involves three primary steps: searching for prey, encircling prey, and attacking prey.

Grey wolves typically live in packs consisting of 5 to 12 individuals. As illustrated in Fig. 1, their social hierarchy is structured from top to bottom, with alpha at the highest rank, followed by beta, delta, and omega. The alpha leads hunting activities, the beta assists with strategic decisions, the delta organizes actions, and the omega follows the directives of the alpha, beta, and delta wolves. In this modeling approach, the first solution is designated as alpha, the second-best solution as beta, the third-best as delta, while all other candidate solutions are classified as omega.

1）Encircling prey

During the hunting process, the grey wolf will encircle prey according to the hunting mechanism. The updated formula of the encircling mechanism is as follows:

$$D = \left| C \bullet X_p(t) - X(t) \right| \tag{1}$$

$$X(t+1) = X_p(t) - A \bullet D \tag{2}$$

The coefficient vectors are calculated as follows:

$$A = 2ar_1 - a \tag{3}$$

$$C = 2r_2 \tag{4}$$

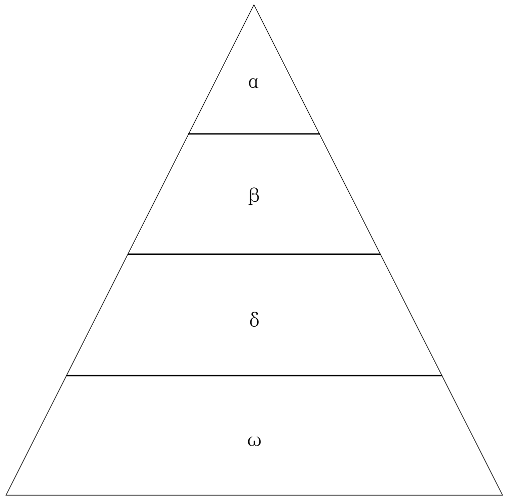

Fig. 1 Hierarchy of grey wolf

2）Hunting

Once the grey wolf encircles its prey, the hunting mechanism is activated based on the wolf's ability to identify the prey. This mechanism is primarily led by the alpha wolves, with beta and delta wolves occasionally contributing to the hunt. To simulate this behavior in the modeled space, it is assumed that the top three candidate solutions possess a better awareness of the prey's potential location. These three solutions are designated as the best solutions, labeled as alpha, beta, and delta, while the remaining candidate solutions (including omega) are saved and updated. The following formula is proposed for the hunting mechanism:

$$\begin{aligned} D_\alpha &= \left| C_1 \bullet X_\alpha - X \right| \\ D_\beta &= \left| C_2 \bullet X_\beta - X \right| \\ D_\delta &= \left| C_3 \bullet X_\delta - X \right| \end{aligned} \tag{5}$$

$$\begin{aligned} X_1 &= X_\alpha - A_1 \bullet D_\alpha \\ X_2 &= X_\beta - A_2 \bullet D_\beta \\ X_3 &= X_\delta - A_3 \bullet D_\delta \end{aligned} \tag{6}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{7}$$

Fig 2 shows how a search agent updates its position in space according to alpha, beta, and delta.

3）Attacking prey

When the grey wolf stops moving it will attack. Since a decreases from 2 to 0 in the iterative process, the value range of the coefficient A is [-a, a]. When the value of A is [-1, 1], it means that the grey wolf is attacking, and the position at the next moment can be anywhere between the current grey wolf and its prey, otherwise it means that the grey wolf is searching for the prey.

4）Search for prey

The location search of the grey wolf algorithm is mainly based on the location of alpha, beta, and delta, which means searching for prey when they are separated and attacking prey when they gather together. When modeling, the value of the random coefficient A is used to judge whether the grey wolf is away from the prey or attacks the prey. When $|A|>1$ means the grey wolf searches for it prey, the GWO algorithm performs a global search. When $|A|<1$, means that the grey wolf is attacking. Another search coefficient in the GWO algorithm is C, which provides a random weight for the prey, with a random value in the range of [0, 2]. The value of C ensures the randomness of the optimization process of the GWO algorithm mechanism and avoids local optimization.

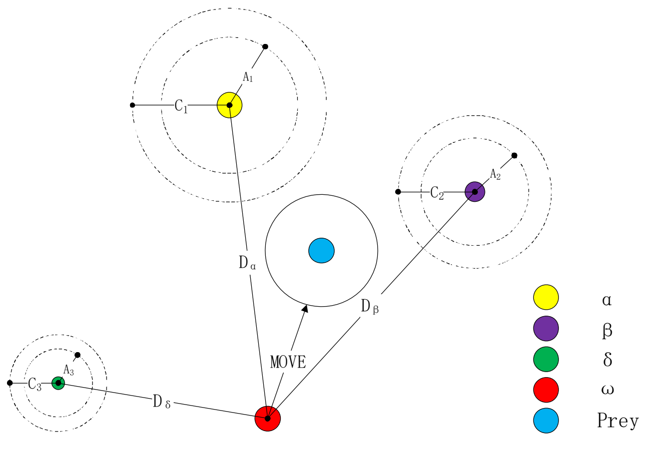

Fig. 2 Position updating in GWO

5）Disadvantages of GWO algorithm

The GWO algorithm is a recent addition to swarm intelligence optimization methods, requiring minimal parameter adjustments, featuring a straightforward structure, and being easy to learn and implement. However, it has several limitations:

(1) SLOW CONVERGENCE

While the unique update method of the GWO algorithm enhances its search capabilities, an increase in the number of iterations leads to a larger data set. As a result, the positions of the alpha, beta, and delta wolves converge, causing only minimal changes in the positions of the omega wolves during the later stages of the process. This can slow down the algorithm's convergence in the final iteration stages.

(2) LOCAL OPTIMUM

With the decrease of a, when some grey wolves in the algorithm fall into the local optimum, other grey wolves in the population will gather around the optimal solution, and the algorithm will not easily jump out when it falls into the local optimum.

(3) LACK OF DIVERSITY

In addition, only the first three optimal solutions are saved at a time in the GWO algorithm. Even though a mechanism like this helps the results to reach to a certain value, it reduces the diversity of the population to some extent.

2.2 Particle swarm optimization algorithm

The particle swarm optimization (PSO) algorithm is a metaheuristic optimization technique grounded in swarm intelligence, proposed by Kennedy and Eberhart. It simulates the foraging behavior of birds, fish schools, and bee colonies, drawing inspiration from artificial life research. During the food search process, organisms may occasionally gather or disperse. In this collective effort, particles within the swarm share information and communicate, facilitating the foraging process and ultimately leading to the discovery of food.

This behavior is inspired by animal foraging to address global optimization problems, where each individual in the population is referred to as a particle. In the PSO algorithm, the initial population is generated randomly. The individual and global positions of the particles are continuously updated and recorded. The formula for updating the particle position is as follows:

$$\begin{aligned} V_i^{k+1} &= V_i^k + C_1R_1(P_i^k - X_i^k) + C_2R_2(G_{best} - X_i^k) \\ X_i^{k+1} &= X_i^k + V_i^{k+1} \end{aligned} \tag{8}$$

Where i represents the i-th particle, k represents the current iteration number, V represents the velocity vector of the particle, X represents the current position of the particle, C_1 and C_2 are learning factors, R_1 and R_2 are random numbers in the interval [0,1], P represents the individual optimum of the particle, and G represents the global optimum of the particle.

2.3 Elite opposition-based learning

Elite opposition-based learning (EOBL) [35] is a commonly used learning strategy to increase the population diversity by constructing the inverse solution of the current solution, which can improve the global search effect in the UUV path planning problem. The main idea is to choose the optimal solution to save by evaluating the current solution and the opposite solution. The definition of the opposite point is given below.

Definition 1 (Opposite point [33]): Assume that there exists a real number x in the interval $[a_i, b_i]$ and that $X_i = (x_1, x_2, \dots x_n)$ is a point in an n-dimensional space (i.e. feasible solution), and $x_i \in [a_i, b_i]$, then its opposite point $\breve{X}_i = (\breve{x}_1, \breve{x}_2, \dots \breve{x}_n)$ is calculated as follows:

$$\breve{x}_i = a_i + b_i - x_i \tag{9}$$

Definition 2 (Elite opposite point [35]): Assume that there exists a real number x in the interval $[a_i, b_i]$ and that $X_i = (x_1, x_2, \dots x_n)$ is a point in the n-dimensional space and $x_i \in [a_i, b_i]$, $k \in (0,1)$ is a random number that obeys the uniform distribution of the interval, then its elite opposite point $\breve{X}_i^e = (\breve{x}_1^e, \breve{x}_2^e, \dots \breve{x}_i^e)$ is calculated as follows:

$$\breve{x}_i^e = k(a_i + b_i) - x_i \tag{10}$$

3. Application of IGWO algorithm to UUV path planning

3.1 Environment Modeling

Accurate ocean information serves as the foundation for UUVs to carry out underwater tasks effectively. The data necessary for UUV path planning must be derived from the terrain model. In this paper, an exponential function is introduced to simulate underwater mountains in the ocean. The mathematical model is expressed as follows:

$$Z(x,y) = \sum_{i=1}^{n} h_i \cdot \exp^{\left[-\left(\frac{x-x_{ci}}{x_{si}}\right)^2 - \left(\frac{y-y_{ci}}{y_{si}}\right)^2\right]} \tag{11}$$

where (x_i, y_i) is the center coordinate of the submarine peak. h_i is the topographic parameter, which controls the height. x_{si}

and y_{si} are the attenuation of the submarine peaks along the x-axis and y-axis directions, respectively, controlling the slope. n represents the total number of peaks. The environmental model of the seamount is shown in Fig 3.

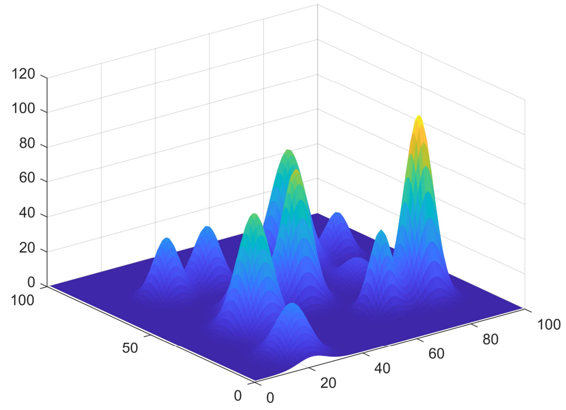

Fig. 3 Environment model

3.2 Binding Conditions

To ensure the effective operation of UUVs, this paper proposes specific constraints for single UUV path planning. First, to address the terrain constraints posed by underwater mountains, the UUV must maintain a working height above these submarine obstacles to avoid collisions during tasks. Second, a defined working area is established to prevent the UUV from going out of bounds while performing underwater activities. Based on these considerations, the environmental constraints are proposed as follows:

$$\begin{cases} 0 < x_i < x_{\max} \\ 0 < y_i < y_{\max} \\ z_0 < z_i < z_{\max} \end{cases} \tag{12}$$

where x_i, y_i and z_i are the specified feasible working area, $x_{\max}$, $y_{\max}$ and $z_{\max}$ are the maximum edges of the working area, and z_0 is the topographic parameter of the submarine mountain range.

3.3 IGWO algorithm

To address the defects of the grey wolf algorithm proposed, this paper introduces the update mechanism Eq. (8) of the particle swarm optimization algorithm to change the Eq. (7) in the grey wolf optimization algorithm to enhance the convergence speed of the algorithm and the ability to jump out of the local optimum, and the updated formula of the grey wolf population after the change is Eq.13. For the updated grey wolf population, the elite opposition-based learning strategy Eq. (10) is used to further enhance the algorithm's convergence speed and the ability to jump out of local optimum. In addition, the introduction of the elite opposition-based learning strategy also enhances the diversity of the algorithm population. The improved grey wolf optimization algorithm enhances the robustness of the algorithm. The algorithm flow chart is shown in Fig 4.

$$\begin{aligned} V_i^{k+1} &= w(V_i^k + C_1R_1(X_1 - X_i^k) + \\ &\quad C_2R_2(X_2 - X_i^k) + C_3R_3(X_3 - X_i^k)) \\ X_i^{k+1} &= X_i^k + V_i^{k+1} \end{aligned} \tag{13}$$

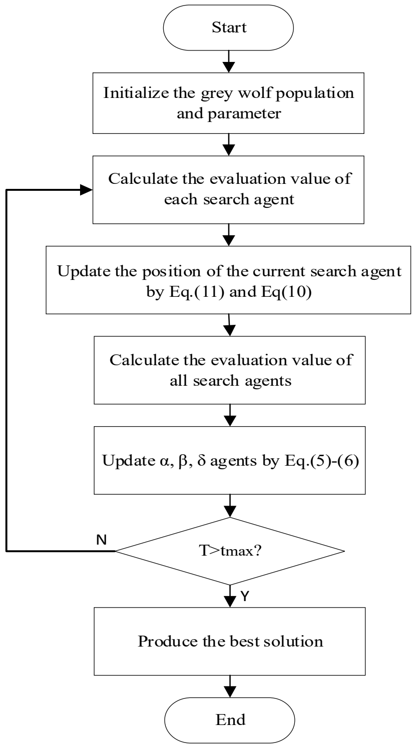

Fig. 4 IGWO algorithm flow chart

3.4 UUV path planning based on IGWO algorithm

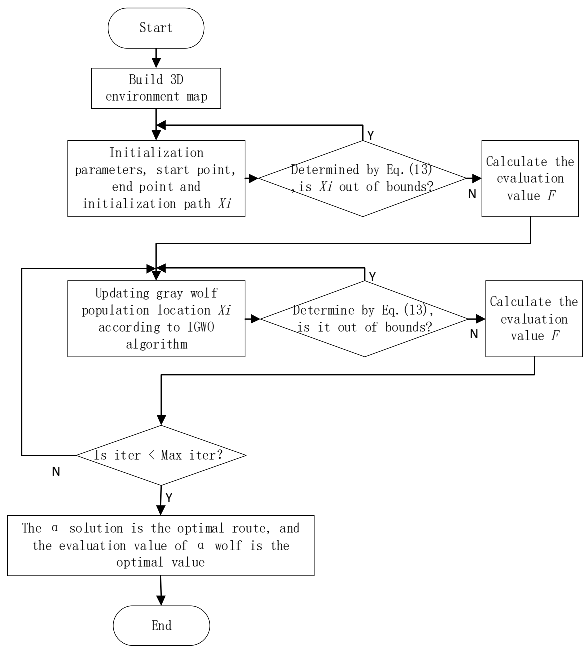

Fig. 5 Flow chart of UUV path planning based on IGWO

3.5 Simulation results and discussions

To verify the feasibility and effectiveness of the IGWO algorithm in UUV path planning, various simulations will be conducted, comparing the IGWO algorithm to GWO, PSO, GWO-PSO [37], and AGWO in different UUV path planning environments. In this study, length is measured in meters, time in seconds, and MATLAB is used for simulations. For consistency, the population size and iteration count in the comparison algorithms are set to match those of the main IGWO algorithm.

1) Different Starting and Ending Points and Environments

The IGWO algorithm's performance is tested across environments with varying obstacle densities, heights, and starting and ending points. Four distinct environment maps are established to assess IGWO's effectiveness: Environment 1: Starting point (S) at (1,100,1) and ending point (G) at (100,1,1), with a population of 20 and a maximum of 100 iterations. Environment 2: Starting at (5,76,5) and ending at (95,30,40), with a population of 30 and a maximum of 150 iterations. Environment 3: Starting at (1,2,100) and ending at (90,90,1), with a population of 30 and a maximum of 200 iterations. Environment 4: Starting at (10,3,2) and ending at (70,70,50), with a population of 40 and a maximum of 250 iterations. Simulation results, including UUV path plots and evaluation function convergence across these four environments, are shown in Fig. 6, Fig. 7, Fig. 8, and Fig. 9.

Scenario 1 simulates the UUV performing some undersea tasks as in Fig 6. The paths obtained by the IGWO algorithm are significantly better than the other algorithms, and the iterations of the IGWO algorithm reach the optimum at 77 iterations according to the iteration plots. As shown in Fig 7 and Fig 8, scenarios 2 and 3 simulate the working paths of the UUV from high to low and from low to high at the starting and ending points, respectively. In both cases, UUV finds a suitable path. In scenarios 2 and 4, it is simulated how the different sparsity of obstacles affects the UUV's work in performing the same type of task from low to high. According to Fig 7 and Fig 9, results show that the IGWO algorithm finds the smoothest path and requires the least number of iterations.

Based on the test results in Fig. 6 to Fig. 9, the IGWO algorithm consistently delivers excellent performance in UUV path planning across scenarios with varying obstacle densities and different start and end point locations. The IGWO algorithm achieves stability within 100 iterations in all four test environments, with GWO-PSO slightly outperforming IGWO in terms of evaluation value only in the third scenario. This demonstrates that, irrespective of environmental changes or start and end point variations, the IGWO algorithm effectively plans superior paths, highlighting its strong adaptability.

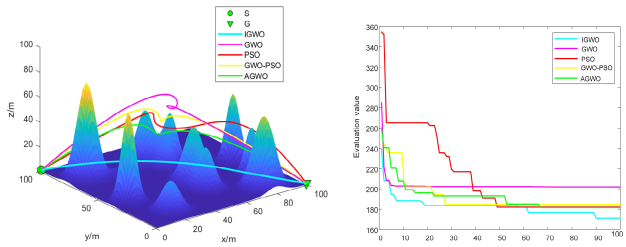

Fig. 6 Scenario 1

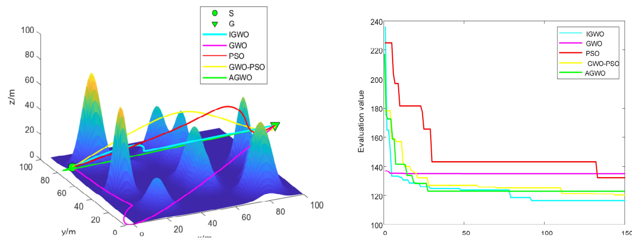

Fig. 7 Scenario 2

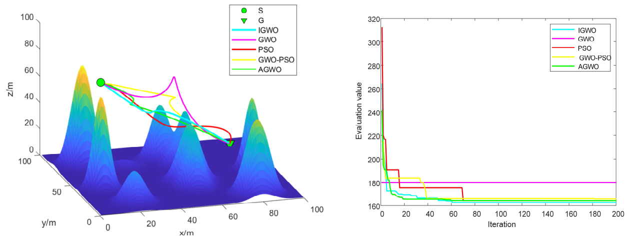

Fig. 8 Scenario 3

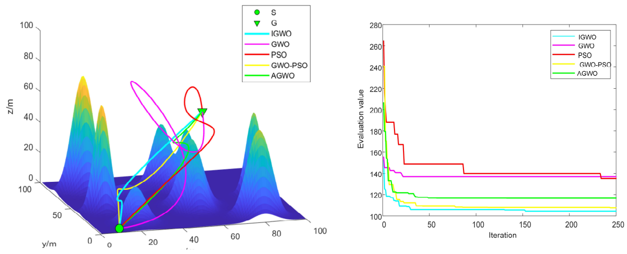

Fig. 9 Scenario 4

2) Different Number of Obstacles

In the previous section, the performance of the IGWO algorithm in UUV path planning was evaluated across environments with varying start and end points. To further assess the effect of obstacle density on UUV path planning using the IGWO algorithm, this section introduces six ocean environments, each with an increasing number of obstacles. The starting and ending points are fixed at (1, 99, 1) and (99, 1, 70). For all six cases, the population size is set to 50, with a maximum of 200 iterations, and obstacle density is increased progressively.

The UUV path simulation results and evaluation function convergence plots for these environments are presented in Fig. 10 to Fig. 15.

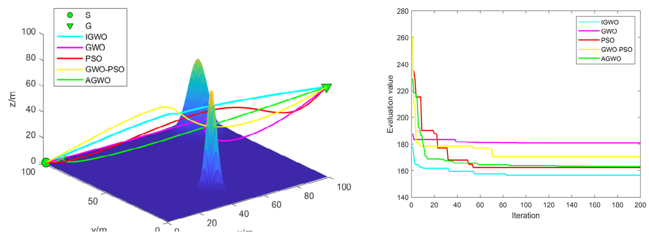

Fig. 10 Scenario 1

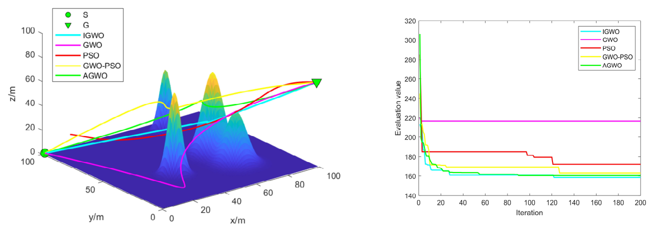

Fig. 11 Scenario 2

According to the path simulation plots in Fig 10-Fig 15, the number of obstacles in each of the six groups of environments increases sequentially, The UUV with the IGWO algorithm is able to avoid obstacles in all six environments to complete the path planning task, while the other four algorithms will have a local optimum. According to the convergence plots of the six evaluation functions in

Fig 10-Fig 15, the evaluation value of IGWO is always minimized and takes less time. In summary, the IGWO algorithm shows strong effectiveness, adaptability, and stability for UUV path planning in environments with different numbers of obstacles.

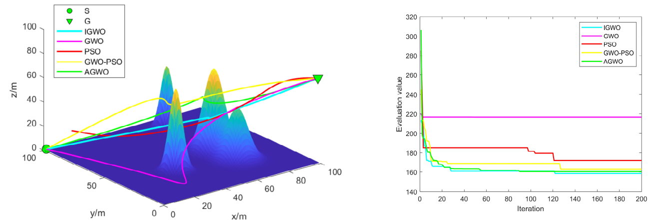

Fig. 12 Scenario 3

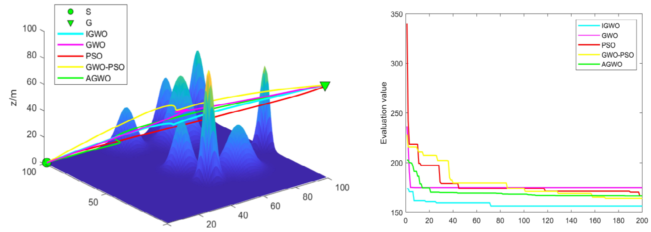

Fig. 13 Scenario 4

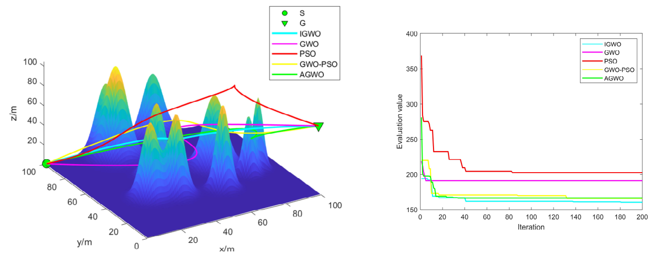

Fig. 14 Scenario 5

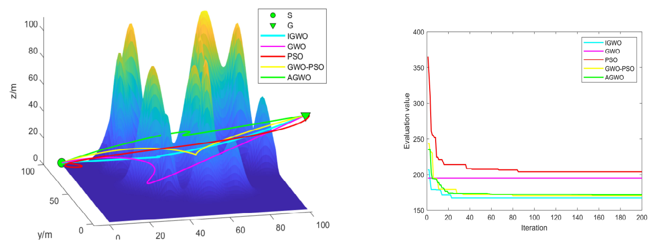

Fig. 15 Scenario 6

4. Summary

This paper introduces an improved GWO algorithm (IGWO) to address the limitations of the standard GWO. First, the PSO algorithm is incorporated to enhance the GWO update formula, increasing the algorithm's ability to escape local optima. Building on this, an elite opposition-based learning strategy is added to further improve search efficiency and convergence speed. The IGWO algorithm is then evaluated for stability and convergence across 23 benchmark functions. Finally, it is applied to UUV path planning, where testing in various 3D environments demonstrates improved convergence speed, stability, and adaptability.

This study also examines hybrid algorithms and single UUV path planning to highlight the advantages of the hybrid approach. Future work will focus on two areas: further refining the hybrid algorithm to address limitations of single algorithms and applying hybrid algorithms to solve the multi-UUV clustering problem, considering UUV operational needs.

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