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Collaborative Searching Strategy for Multi-Amphibious Spherical Robots in 3D underwater environments

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Abstract **- An improved multi-robot cooperative strategy based on the improved artificial bee colony algorithm is proposed for the task of underwater multi-robot cooperative area target search. The strategy consists of three stages: cruising stage, building capture alliance stage, and cooperative search stage. In the cruising stage, robot adopts the improved random walk algorithm for aimless cruising. In the building capture alliance stage, robot uses an auction algorithm for the assignment of search tasks. In the cooperative search stage, robot adopts the improved artificial bee colony algorithm for cooperative search of targets. Furthermore, simulations are conducted, and the results demonstrate that the proposed strategy can effectively guide multiple robots to perform area target search in unknown 3D underwater environments.**

Index Terms - Multi-robot system, Amphibious spherical robot, Collaborative searching.

I. INTRODUCTION

Underwater target search is an important task for underwater robots in various applications such as scientific research, ocean exploration, and military operations [1]. In recent years, the development of collaborative search among multiple underwater robots has become a research focus in the field of underwater robotics [2,3]. In particular, the collaborative target search of multiple underwater robots in three-dimensional unknown underwater environments has become an intensively researched direction [4].

To deal with the complexity of underwater environments, decentralized control strategies have been introduced in recent years. In the decentralized control strategy, multiple underwater robots exchange information and make decisions in a decentralized manner [5]. For example, researchers have proposed a distributed method for collaborative search of multiple underwater robots based on consensus algorithms, where each underwater robot communicates with its neighbors and shares its location information to reach consensus [6,7].

In addition, some researchers have introduced advanced optimization algorithms to improve the search paths of multiple underwater robots in collaborative search. Among them, some researchers have applied the grey wolf algorithm to optimize the motion path [8,9], and others have conducted in-depth research on path planning in 3D environments [10].

Furthermore, some researchers have introduced advanced optimization algorithms to improve the efficiency and effectiveness of collaborative search among multiple underwater robots [11]. Among them, some researchers have conducted in-depth research on trajectory tracking of underwater robots and used dynamic optimization algorithms to optimize the search trajectory of underwater robots [12]. In addition, some researchers have applied an improved artificial potential field algorithm to multi-robot underwater target encirclement which shown in Figure 1[13]. The study of fluid mechanics models can help predict changes in water flow and underwater environments, improving the control accuracy and robustness of underwater robots in complex environments [14,15]. The application of these technologies will greatly promote the development and practical application of collaborative search among multiple underwater robots.

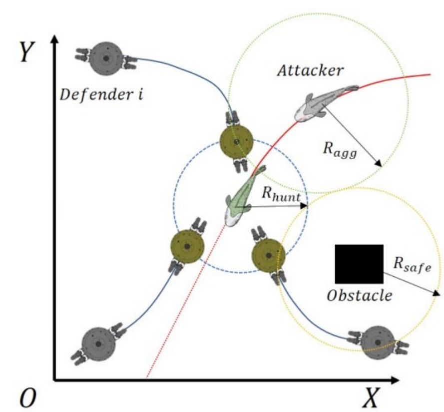

Fig. 1 Schematic diagram of multi machine encirclement [13]

At the same time, some researchers have explored the integration of artificial intelligence technologies such as reinforcement learning and neural networks in underwater robot search. Among them, researchers have proposed a deep reinforcement learning method for coordinating multiple underwater robots in search tasks, which performs better than traditional methods [16].

Cooperative search methods for multiple autonomous underwater vehicles (AUVs) can be divided into two types based on target information: one based on known target prior distribution, such as heuristic search methods, and the other based on sensor information without any target information, such as area search methods [17].

This paper focuses on the cooperative search task based on sensor information using swarm intelligence algorithms, and proposes a comprehensive system solution consisting of three phases: random cruising phase, alliance formation phase, and collaborative search phase. First, an improved random walk algorithm is proposed for multiple AUVs to cruise underwater and obtain target information. Once target information is detected, an improved auction algorithm is used to form search alliances. Finally, an improved artificial bee colony algorithm is used to determine the path of each AUV in searching for the target.

The main contributions of this paper can be summarized as follows: a system solution is proposed for multiple AUVs to collaboratively search for targets in an unknown underwater 3D environment. In this solution, a mixed rule evaluation function is designed in the random walk algorithm based on the specific underwater environment and robot motion characteristics, and a self-adaptive location selection method is designed in the artificial bee colony algorithm. Finally, the feasibility and efficiency of the proposed algorithm are demonstrated by comparing it with classical particle swarm optimization and artificial bee colony algorithms.

The organization of this paper is as follows: Section 2 introduces the problem description. Section 3 presents the improved artificial bee colony-based method for cooperative search by multiple underwater robots. Section 4 provides simulation results and analysis. Finally, conclusions are given in Section 5.

II. PROBLEM DESCRIPTION

The search task of this paper is to use multiple AUVs to search for targets in a specific area in an underwater environment. To simplify the underwater environment and AUVs state, the following assumptions are made:

a. AUVs are denoted as $A_i\{i = 1, 2, ..., N\}$, and target points are denoted as T_i $\{i = 1, 2, ..., M\}$, where N is the number of all AUVs and M is the number of all target points.

b. The position of each target point is unknown to each AUV, and AUVs can communicate and share data with each other. AUVs can be considered as circular robots with a small radius, and their moving speed dynamically changes within a reasonable range.

c. Each target point emits information (such as radiation from a radioactive source) into the underwater environment, and its information intensity is defined by formula 1：

$$S(T_i, POS_j) = \begin{cases} I_{max}, \ DIS(POS_{T_i}, POS_j) \leqslant DIS_{min} \\ \frac{I_{max}}{DIS(POS_{Ti}, POS_j)}, DIS_{min} < DIS(POS_{T_i}, POS_j) \leqslant DIS_{max} \\ I_{min}, DIS(POS_{T_i}, POS_j) > DIS_{max} \end{cases} \quad (1)$$

Among them, POS_{T_i} represents the position of the target point T_i , POS_j represents the position of AUV j, $DIS(POS_{T_i}, POS_j)$ represents the distance from AUV j to the target point I, DIS_{min} is the minimum threshold for the defined distance, DIS_{max} is the maximum threshold for the defined distance, I_{min} is the minimum information intensity received by the AUV, I_{max} is the maximum information intensity received by the AUV.

d. When the distance between the position of AUV POS_j and the position of target point POS_{T_i} is less than the defined minimum distance DIS_{min}, the AUV receives the maximum information intensity I_{max}. The situation is similar for other positions. When the AUV receives an information intensity greater than I1, it will perceive the existence of the target, and when the AUV receives an information intensity greater than I2, it will lock onto the target.

The simplified model for multi AUV search in this paper is shown in Figure 2.

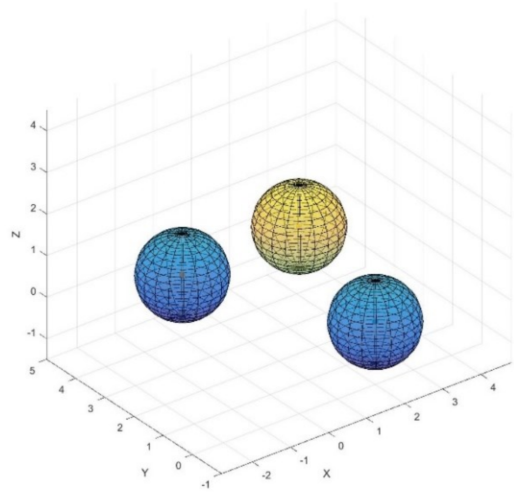

Fig. 2 Search Simplified Model

The search process of this article is divided into three stages, and the basic flowchart is shown in Figure 3. The following section will provide a detailed explanation.

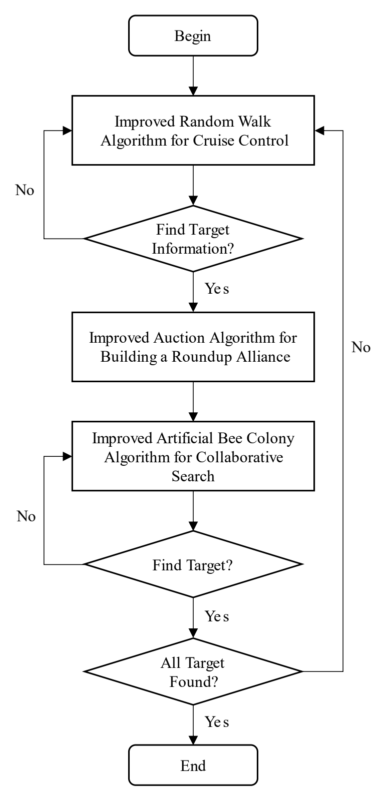

Fig. 3 Overall search flowchart

III. SOLUTION

The collaborative search task of multiple AUVs can be completed in three stages: (1) random cruise search for targets; (2) Establish a dynamic search and capture alliance to the target location; (3) Search for target location based on target information. Based on this, this article proposes a multi robot collaborative target search method based on an improved artificial bee colony algorithm.

Below is an explanation of some variable representations used in the algorithm in this article:

A flag represented by $g(A_i)$ indicates the state of the AUV as cruising, searching, or locking. Another flag represented by $g(T_i)$ indicates the state of the target as unknown, known, or locked:

$$g(A_i) = \begin{cases} A_x, \ AUV \text{ is cruising} \\ A_y, AUV \text{ is finding a target} \\ A_z, \ AUV \text{ is searching for a target} \end{cases} \tag{2}$$

$$g(T_i) = \begin{cases} T_x, \text{Target is unknown} \\ T_y, \text{Target is noticed} \\ T_z, \text{Target is searched} \end{cases} \tag{3}$$

A. Cruising stage based on improved random walk

At initialization, all AUV flags are set to $g(A_i) = A_x$, and all target flags are set to $g(T_i) = T_x$. Initially, the positions of AUVs are randomly distributed in the underwater environment, with position $P = \{p_1, p_2, ..., p_n\}$, where n is the number of robots. AUVs cannot obtain target information in the environment at the beginning, so they are set to the cruising stage, and the memorization list is $L = \{\}$. For each robot *i*, the following random walk search process is performed: the current robot is at p_i, a random direction $\vec{d_i}$ and step length d are selected, and the next position p_{i+1} is calculated:

$$p_{i+1} = p_i + \vec{d_i} \cdot d \tag{4}$$

If the new position p_{i+1} is already in the memorization list, skip that position and generate a new position based on Equation (1). Otherwise, calculate the evaluation value of the new position and compare it. However, the general evaluation function is not suitable for the movement of AUVs. For example, AUVs may collide with obstacles or other AUVs, or their actions may exceed the potential area of the target. Therefore, this paper designs a hybrid rule evaluation function for small spherical amphibious robots, which has the following structure:

$$E(P) = S(T_i\,, P) - CrashCheck\ (P) \tag{5}$$

Among them, $E(P)$ represents the evaluation value of position P, and $S(T_i\,, P)$ represents the information intensity of position P at time *i*, $CrashCheck$ represents the collision detection value of position P.

If the evaluation value of the new position is better than the current position, update the current position to p_{i+1};otherwise, accept the new position with a certain probability (such as Boltzmann probability) and update the current position to p_{i+1}. The Boltzmann probability calculation formula is:

$$U(\Delta E) = e^{-\frac{\Delta E}{T}} \tag{6}$$

where $\Delta E = E(p_{i+1})$ - $E(p_i)$ is the difference in evaluation values between the new and old positions, and T is the temperature parameter that controls the probability size.

$$p_i \leftarrow \begin{cases} p_{i+1}, & \text{with probability } U(\Delta E) \\ p_i, & \text{otherwise} \end{cases} \tag{7}$$

Specifically, in this stage, all AUVs with $g(A_i) = A_x$ randomly cruise within the search area to discover target information. If an AUV a detects target information, its flag is set to $g(A_i) = A_y$, and the flag of the detected target T_i is marked as $g(T_i) = T_y$.

B. Construction of the search and capture alliance based on auction algorithm

In this stage, assuming there are *n* AUVs with $g(A_i) = A_y$ and *m* target points with $g(T_i) = T_y$, the task allocation problem between *n* AUVs and *m* target points needs to be solved. The auction algorithm has advantages such as efficiency, flexibility, scalability, and adaptability, which can effectively solve the allocation problem of multiple AUVs and multiple target points.

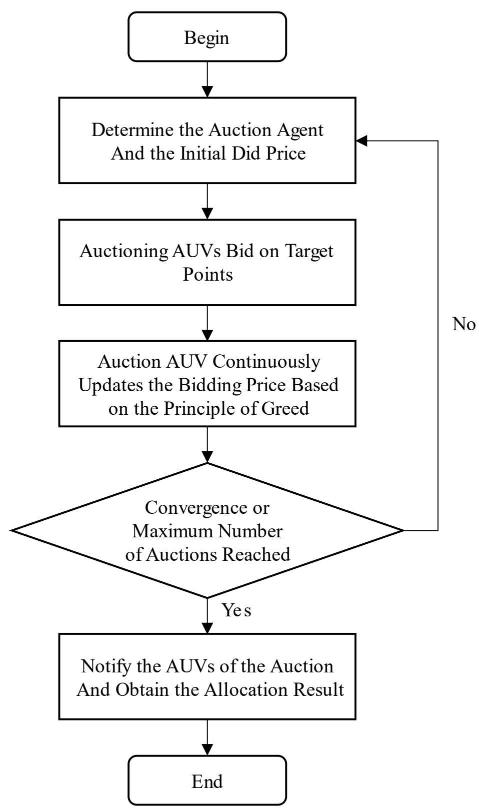

Fig. 4 Auction algorithm flowchart

This article proposes a construction scheme of the search and capture alliance based on the auction algorithm. The auction algorithm is essentially a search tree algorithm, consisting of auction agents and bidding agents. Its basic idea is that m target points are auctioned by *n* AUVs. Assuming that the value of the *i* target point is V_i, and the cost that AUV *j* needs to pay to reach the target point is C_j, the profit obtained is $G_{ij} = V_i - C_j$. For all AUVs, the auction stops when the overall profit is maximized. The basic process is shown in Figure 4.

According to the research objectives of this article, it can be assumed that the profits of all target points are the same and equal to a constant, and the cost that the AUV needs to pay to reach the target point is the estimated distance. Unlike traditional auction algorithms, this article allows multiple AUVs to bid for the same target point, and this group of AUVs will form a search and capture alliance to conduct detailed search on the target point.

C. Collaborative search phase based on improved artificial bee colony algorithm

In this phase, each AUV in the search coalition will collaboratively search for the same target. Assuming the communication between the AUVs in the same coalition is unobstructed, they will search for the specific location of the target through changes in the information strength at the target point, which can be abstracted as a combinatorial optimization problem. Considering the complexity of the underwater 3D environment and the diversity of multi-AUV collaboration, this paper proposes an improved artificial bee colony algorithm for multi-AUV collaborative area target search.

The artificial bee colony algorithm is used because it has faster search speed than traditional swarm intelligence algorithms, requires fewer iterations to achieve convergence, and is more suitable for scenarios with high real-time requirements underwater. In order to make the artificial bee colony algorithm more effective in collaborative target search, this paper has made some improvements specifically for AUVs.

In the proposed algorithm based on improved artificial bee colony, each AUV in the underwater environment represents a bee and moves in the three-dimensional search space. The fitness function Fitness(p) is the basis for judging whether a position is better or not, and is defined as follows:

$$FIT(P) = \sum_{i=1}^{M} S(T_i, P) - \mathrm{crashCost}(P) \tag{8}$$

The definition of $\mathrm{crashCost}(P)$ is as follows: Obstacle(P) is used to determine whether there are obstacles at position P, AUV(P) is used to determine whether there are AUVs at position P, and Range (P) is used to determine whether position P exceeds the search area.

$$\mathrm{crashCost}(P) = \begin{cases} 1, \mathrm{Obstacle}(P) \text{ is True} \\ 0, \mathrm{Obstacle}(P) \text{ is False} \end{cases} + \begin{cases} 1, \mathrm{AUV}(P) \text{ is True} \\ 0, \mathrm{AUV}(P) \text{ is False} \end{cases} + \begin{cases} 1, \mathrm{Range}(P) \text{ is True} \\ 0, \mathrm{Range}(P) \text{ is False} \end{cases} \tag{9}$$

At initialization, *N* candidate positions are randomly generated, and the fitness function value is calculated. The top 50% of the positions are selected as high-potential positions, and the bottom 50% are selected as low-potential positions. The number of candidate positions is always *N* and does not change with iteration. The specific randomly generated candidate positions are as follows:

$$P^j = P_{\min}^j + \mathrm{rand}\,(0,1)\left(P_{\max}^j - P_{\min}^j\right) \tag{10}$$

Where P^j belongs to {*X, Y, Z*} and is a component of the three-dimensional solution vector, and $P_{\max}^j$ and $P_{\min}^j$ are the maximum and minimum values that the AUV can reach in this dimension within one step. The scout AUV remembers its previous optimal solution and searches in the neighborhood of the high-potential position. The search formula is:

$$Q_{ij} = P_{ij} + \varphi_{ij}\left(P_{ij} - P_{kj}\right) \tag{11}$$

Where *j* belongs to {1,2,3}, *k* belongs to {1, 2, …, *N*}, *k* is randomly generated and $k \neq i$, φ_{ij} is a random number between [-1,1]. As the number of iterations accumulates, the distance between $\left(P_{ij} - P_{kj}\right)$ decreases, the search space also decreases, that is, the step size of the search decreases dynamically, which helps the algorithm to improve its accuracy and eventually obtain the optimal solution, or a suboptimal solution very close to the optimal solution.

The scout AUV uses a greedy selection method to compare the optimal solution in memory with the neighborhood search solution. When the search solution is better than the optimal solution in memory, it replaces the memory solution; otherwise, it remains unchanged.

After all scout AUVs complete neighborhood search, they share position information with the backup AUVs. The backup AUV selects positions based on the information with a certain probability, and the probability of selecting positions with higher fitness function values is higher.

Similarly, the backup AUV performs a neighborhood search in the position it selects, using a greedy criterion to compare the solution obtained by the search with the solution corresponding to the original position, and replacing the original solution with the search solution if it is better, completing the role exchange; otherwise, it remains unchanged. In the ABC algorithm, the calculation formula for backup AUV to determine the selection probability is:

$$Possibility_i = \frac{FIT(P_i)}{\sum_{k=1}^{sum} FIT(P_k)} \tag{12}$$

In the equation, $FIT(P_i)$ represents the fitness function value of the *i*-th solution. The probability of selecting each position is proportional to its fitness function value.

If the vanguard AUV gets trapped in a local optimum, i.e., the position remains unchanged for *Limit* iterations, and the fitness obtained by the vanguard AUV is not the current global optimum, then the position is abandoned and replaced with a new position obtained by random search from a spare AUV.

Throughout the entire iterative process, all AUVs will move along the new position until the target *T* is found. Otherwise, the artificial bee colony algorithm will re-enter the search phase.

IV. Simulation and Experiment

In order to demonstrate the effectiveness of the proposed method in multi AUV collaborative target search in unknown three-dimensional environments, some simulations were conducted on a computer on the MATLAB platform. In order to simplify the implementation, the assumptions in this study are as follows:

a. AUV and target are assumed to be regular spheres of the same size.

b. AUV's endurance can meet the entire search process.

c. The positions of AUV, obstacles, and search targets are randomly generated in a 3D underwater environment.

d. Communication between AUVs is not delayed.

Figure 5 shows the initialization state, randomly generating the position information of the search robot and the target point. The robot coordinates are A1 (10, 80, 10), A2 (15, 70, 80), A3 (80, 10, 80), A4 (90, 10, 10), A5 (30, 30, 30), A6 (77, 28, 10), and the coordinates of the two target points are (42, 53, 10) and (73, 37, 50), respectively.

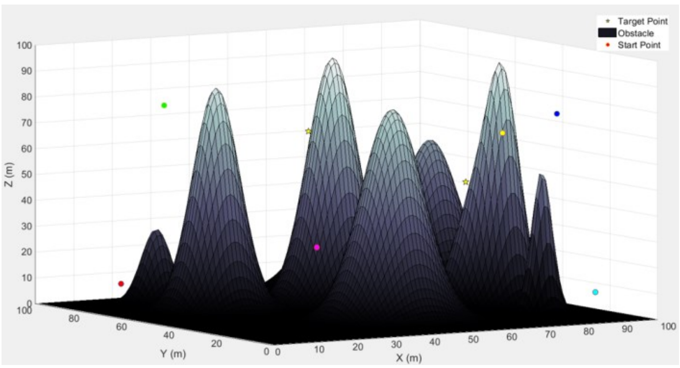

Fig. 5 Initial search graph

In order to test the basic performance of the proposed method, the first simulation of searching for static targets was conducted. The search process based on the proposed improved artificial bee colony method is shown in Figure 6.

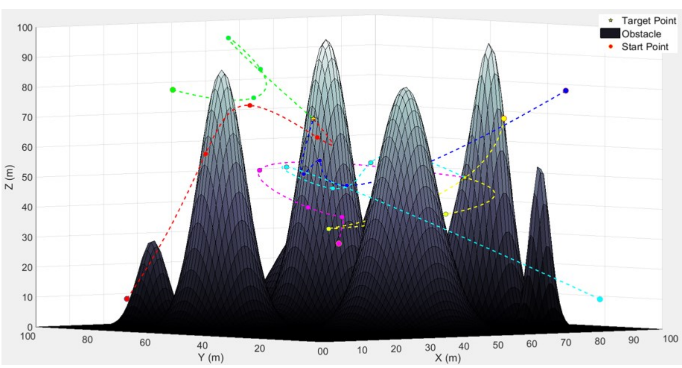

Fig. 6 Initial iteration diagram

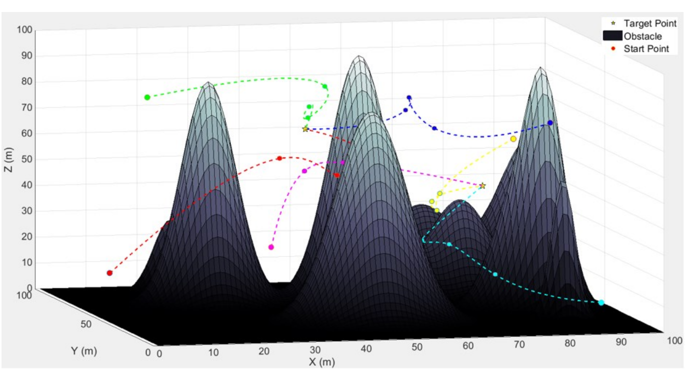

Fig. 7 Iterative Tenfold Graph

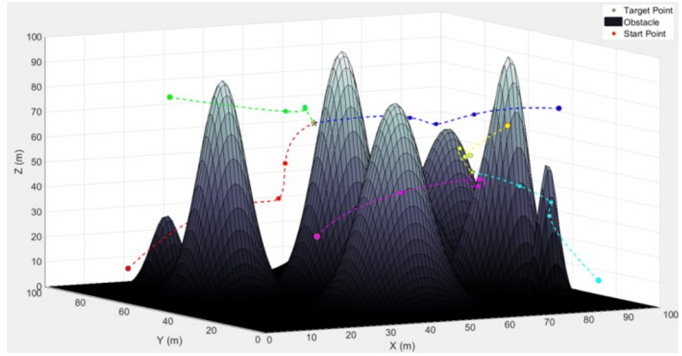

Fig. 8 Iterative Graph Thirty Times

Figures 7, and 8 show the search results after 10 and 30 iterations, respectively. Figure 9 is a top view of the optimal path.

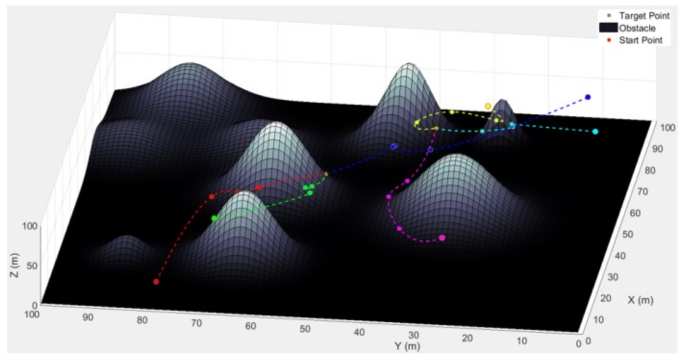

Fig. 9 Final iteration result

The results in Figure 9 indicate that the proposed method can effectively locate the target. Firstly, AUVs are unaware of obstacles and targets in the underwater environment, so each AUV randomly cruises in the underwater environment. Then, the AUV detects the information of the target point and forms an alliance of three AUVs to search for the target point (Figure 6). When the target is found and locked by one of the AUVs (Figure 8), the other two AUVs in the alliance randomly cruise again to search for other targets. Finally, two targets were found and the search task was completed (Figure 9).

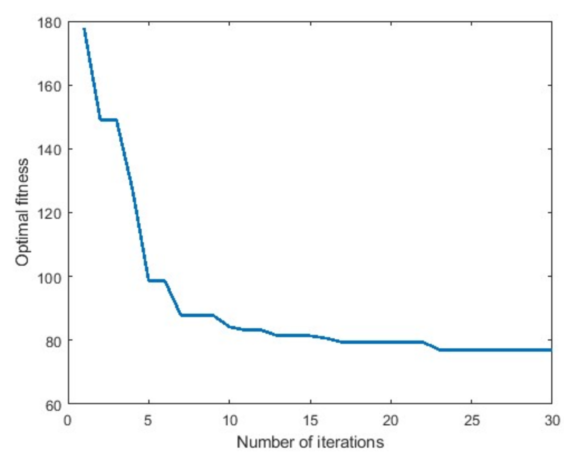

Fig. 10 Graph of Iterations and Optimal fitness

As shown in Figure 10, the whole algorithm has a fast iteration speed. When it iterates to 20 times, it is basically close to the optimal fitness. This advantage will bring great convenience for the algorithm to be used in the real underwater environment.

The results of the comparative experiment are shown in Table I.

TABLE I
COMPARATIVE EXPERIMENT

Method	Fitness	Iterations	Cost time(s)
I-ABC	42.37	31	5.26
ABC	45.60	37	7.69
PSO	42.02	34	6.45

It can be seen that all three methods can effectively complete the task of multi robot collaborative search in underwater environments. However, it can be seen that the improved artificial bee colony algorithm proposed in this paper has advantages such as fast iteration speed, excellent generated solution quality, and ease of application.

V. CONCLUSION

This article aims to study the collaborative search problem of multi robot systems in unknown three-dimensional underwater environments. Firstly, the improved random walk algorithm is used to make all AUVs cruise randomly in the underwater environment; Then, when a robot discovers the location of the target point, an improved auction algorithm is used to construct a search and capture alliance for the target point based on the target location; Finally, the search capture alliance utilizes an improved artificial bee colony algorithm to achieve path planning to the target location, in order to complete the entire search behavior. The algorithm proposed in this article fully considers the motion characteristics of AUVs. Simulation results show that this algorithm can effectively achieve capture tasks in three-dimensional complex environments and has high applicability.

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