An improved ant colony optimization algorithm based on particle swarm optimization algorithm for path planning of autonomous underwater vehicle

Article *in* Journal of Ambient Intelligence and Humanized Computing · August 2020

DOI: 10.1007/s12652-019-01531-8

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Journal of Ambient Intelligence and Humanized Computing
https://doi.org/10.1007/s12652-019-01531-8

ORIGINAL RESEARCH

An improved ant colony optimization algorithm based on particle swarm optimization algorithm for path planning of autonomous underwater vehicle

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Received: 19 December 2018 / Accepted: 27 September 2019

Abstract
The motion control of autonomous underwater vehicle (AUV) has got more and more attention because AUV has been used in many applications in recent years. In order to find the optimal path for AUV to reach the specified destination in complex undersea environment, an improved ant colony optimization (ACO) algorithm based on particle swarm optimization (PSO) algorithm is proposed. Due to the various constraints, such as the limited energy and limited visual distance, the improved ACO algorithm uses improved pheromone update rule and heuristic function based on PSO algorithm to make AUV find the optimal path by connecting the chosen nodes of the undersea environment while avoiding the collision with the complex undersea terrain (static obstacles). The improved ACO algorithm based on PSO algorithm can overcome disadvantages of the traditional ACO algorithm, such as falling into local extremum, poor quality, and low accuracy. Experiment results demonstrate that improved ACO algorithm is more effective and feasible in path planning for autonomous underwater vehicle than the traditional ant colony algorithm.

Keywords AUV · Path planning · ACO algorithm · PSO algorithm · Pheromone · Path point

1 Introduction

Due to the potential technical superiority, AUV has been widely used in commercial, scientific and military applications, such as offshore oil and obviating torpedoes and so on (Yuh 2000; Xiang et al. 2015; Santhakumar and Asokan 2013). In these applications, high precision is usually required to accomplish the specific tasks. The problem of path planning in completely unknown undersea environment is an important branch of AUV research. An obstacle-avoided optimal path is required for AUV from start point to goal point in the complex undersea environment to solve the path planning problems.

All the existing path planning methods are mostly in two-dimensional plane (Chen et al. 2013b; Ghoseiri and Nadjari 2013; Mousavi et al. 2017; Tan et al. 2007). The design of path planning algorithm in three-dimensional plane is difficult due to its complicated calculation process, large amount of stored information, difficulty in directly performing global planning, and other issues. Many algorithms have been proposed to solve the path planning problems in three-dimensional space and get some good results, such as artificial potential field algorithm (Sun et al. 1993), A* algorithm (Carroll et al. 1992), genetic algorithm (Hao and Zhang 2003), and PSO algorithm (Chen et al. 2013a). However, they have some limitations. The artificial potential field algorithm can be trapped in local optimal path easily with the complicated optimization. The A* algorithm can not meet the space-time requirement when the dimension increases. When the environment is complex, the genetic algorithm is difficult to find a feasible path. The PSO algorithm is quasi three-dimensional planning algorithm.

ACO algorithm is a new intelligent optimization algorithm (Blum 2005; Narasimha et al. 2013; Reed et al. 2014; Arora et al. 2019). ACO algorithm has many characteristics, such as swarm intelligence, positive feedback mechanism and distributed computing. It can be used two-dimensional or three-dimensional path planning. However, the traditional ACO algorithm falls into local extremum

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Published online: 23 October 2019

easily and has poor quality and low accuracy in the three-dimensional path planning.

1.1 Major contributions

In this paper, an improved ACO algorithm based on PSO algorithm is proposed which uses ACO algorithm to obtain the global optimal solution for the local optimal problem caused by premature particle in PSO algorithm. The main contributions of this paper are given as follows.

- An improved ACO algorithm using the improved pheromone update rule and heuristic function based on PSO algorithm (Mousavi et al. 2017) is designed to make AUV find the optimal path.
- Due to various constraints, the algorithm design considers two aspects: one is the execution time of algorithm, and the other is the length of path.
- In the three-dimensional undersea environment, the static obstacles are considered.

This paper is organized as follows.

In Sect. 2, three-dimensional undersea environment model is given. In Sect. 3, the improved ACO algorithm based on PSO algorithm for AUV in three-dimensional undersea environment is designed. In Sect. 4, the improved ACO algorithm applied to obstacle-avoided path planning for AUV is presented. To show the effectiveness of the proposed approach, comparative simulations between the improved ACO algorithm and the traditional ACO algorithm are performed. Finally, conclusions are made in Sect. 5.

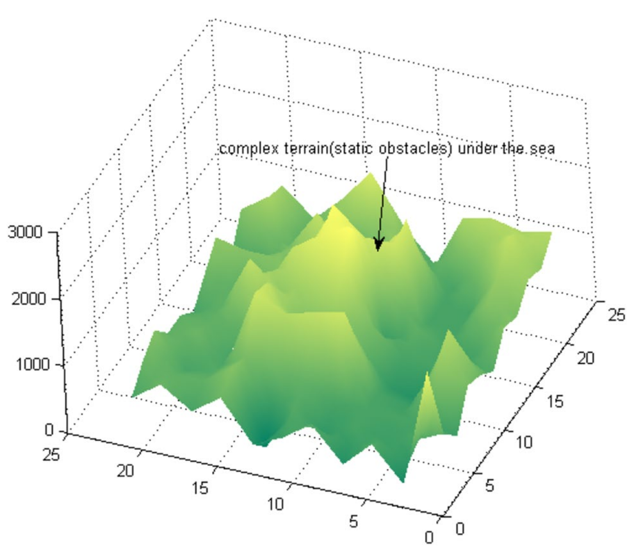

Fig. 1 Undersea terrain space

2 Three-dimensional undersea environment model

The three-dimensional undersea environment model is constructed as shown in Fig. 1.

In order to solve the path planning problem, the uniform mesh method is used to get three-dimensional undersea mathematical model. The method is described as follows:

Firstly, the coordinate system is established as shown in Fig. 2. The x-axis follows the longitude degree increment direction and passes point O in the water level. The y-axis follows the latitude degree increment direction and passes point O in the water level. The z-axis follows the upward direction and passes point O which is perpendicular to the water level.

Secondly, the path planning space is established as shown in Fig. 2. In the coordinate system, O-xyz takes point O as a vertex, takes the maximum length $|OO'|$ along the z-axis as the edge of a cube, takes the maximum length $|OA|$ along the x-axis as the edge of a cube and takes the maximum length $|OC|$ along the y-axis as the edge of a cube. Then, the cube space $OABC$-$O'A'B'C'$ can be obtained.

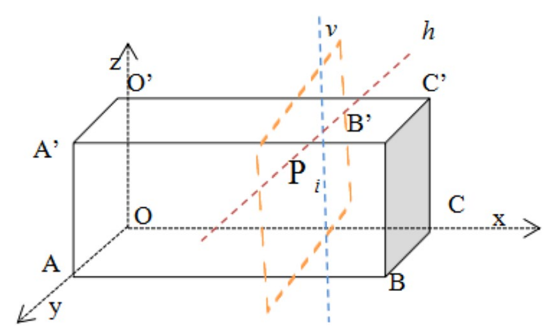

Fig. 2 Path planning space

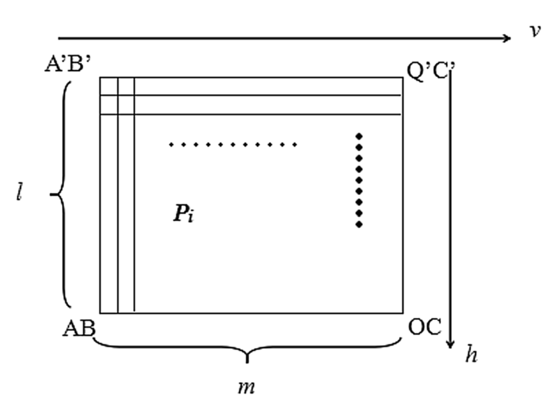

Fig. 3 Planar graph partition

Finally, the path planning space is divided into grids to the abstract undersea model as shown in Fig. 3. The path planning space is plotted into n parts along line OA to obtain $n+1$ planes P_i $(i = 0, 1, \ldots, n)$. Then, arbitrary plane P_i is plotted into m parts along line v and is plotted into l parts along line h .

Through the uniform mesh method, the path planning space $OABC\text{-}O'A'B'C'$ is dispersed into many three-dimensional grid-points and $P*$ is the set of these points. Any point in the set $P*$ corresponds to two coordinates, namely sequence number coordinate $N(i, j, k)(i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, m; k = 1, 2, 3, \ldots, l)$ and position coordinate $n(x_i, y_j, z_k)$. The sequence number coordinate $N(i, j, k)$ is the sequence number along the three directions in the process of plotting space. The position coordinate $n(x_i, y_j, z_k)$ is longitude excursion distance, latitude excursion distance, and depth excursion distance of the position corresponding to point O.

The relationship between point n and point N satisfies:

$$\begin{bmatrix} x_i \\ y_i \\ z_i \end{bmatrix} = \begin{bmatrix} \lambda_1 & \lambda_2 & \lambda_3 \end{bmatrix} \cdot \begin{bmatrix} i \\ j \\ k \end{bmatrix} \tag{1}$$

Let $\lambda = [\lambda_1 \quad \lambda_2 \quad \lambda_3]$, then Eq. (1) can be described

$$n = \lambda \cdot N \tag{2}$$

where λ is the transfer vector from the sequence number coordinate to position coordinate.

The improved ACO algorithm is used in this three-dimensional obstacle-avoided path planning to establish an optimal path between the start point and the goal point according to certain criteria.

3 Improved ACO Algorithm based on PSO algorithm

3.1 Visual domain space of AUV

The three-dimensional undersea environment model has divided the entire search space into a series of discrete points that include obstacle points. When AUV moves from the current point to the next point, the search area is limited to the visual domain space, which can improve the search efficiency of improved ACO algorithm.

Assumption 1 The main direction of three-dimensional path planning is along the x-axis direction. The AUV moves along the x-direction. To reduce the complexity of path planning, the AUV movements are simplified through three direction:forward, transverse and longitudinal movement.

According to the movement characteristics of AUV, the definition of AUV visual domain region is provided as follows:

Definition 1 When the AUV moves forward one unit L_x from point N_{now} in plane P_i, it is allowed the ant to take the maximum transverse movement L_y and to take the maximum longitudinal movement L_z. Here, L_x represents the maximum visual distance of the ant along x-axis direction. Γ is the selection domain in the rectangular plane P_{i+1} that contains the ant next path points set $allowP*_{i+1}$.

The area of rectangular selection domain Γ as shown in Fig. 4 satisfies:

$$\Gamma = L_y \cdot L_z \tag{3}$$

$$L_y \approx 2L_x \cdot \sin|\theta| \tag{4}$$

$$L_z \approx 2L_x \cdot \sin|\psi| \tag{5}$$

where θ is the pitch angle of AUV and satisfies that $\theta_{min} \le \theta \le \theta_{max}$; θ_{min} and θ_{max} are lower bound vale and upper bound value of pitch angle respectively and $|\theta_{min}| = |\theta_{max}|$; ϕ is the yaw angle of AUV and satisfies that $\phi_{min} \le \phi \le \phi_{max}$; ϕ_{min} and ϕ_{max} are lower bound vale and upper bound value of yaw angle respectively and $|\phi_{min}| = |\phi_{max}|$.

Thus, according to Eqs. (2), (4) and (5), the sequence number coordinate of the rectangular points set $N(i, j, k)$ is given as follows:

$$\begin{cases} i = 1, 2, 3, \ldots, n \\ j = \max\left(j - \frac{L_y}{2\lambda_2}, 0\right), \ldots, \min\left(j + \frac{L_y}{2\lambda_2}, m\right) \\ k = \max\left(k - \frac{L_z}{2\lambda_3}, 0\right), \ldots, \min\left(k + \frac{L_z}{2\lambda_3}, l\right) \end{cases} \tag{6}$$

In the improved ACO algorithm, the path search is conducted according to the probability. A different decision rule is used which is called improved pseudo-random

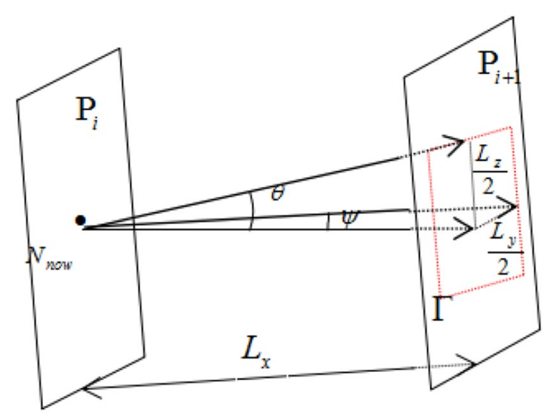

Fig. 4 AUV visual domain

proportional rule. This rule can use the distance heuristic information between the points as well as pheromone prior knowledge that is already stored, and can have a propensity to explore. The following process shows how ants in the present point N_{now} in plane P_i choose the next path point N_{next} in plane P_{i+1}.The feasible path points in the selection space of plane P_{i+1} are chosen according to the three-dimensional undersea environment model. The improved heuristic information value of an arbitrary point N_{next} in the selection space of plane P_{i+1} is calculated.

3.2 Design of improved heuristic function

Heuristic function is an important component of the path planning algorithm in three-dimensional space. This function calculates the three-dimensional path selection probability of each point within the visible area ants searching from the current point N_{now} in plane P_i to the next point N_{next} in plane P_{i+1}. The heuristic function is not only the carrier of characterization of future information but is also an important part of the three-dimensional path planning algorithm. The heuristic function must ensure that the improved ACO algorithm searches the global optimal solution within a reasonable period of time. An improved heuristic function based on PSO algorithm is given as follows:

$$\begin{aligned} H^k_{N_{now},N_{next}}(t) &= S(t)\cdot(r_1\cdot\eta_1\cdot D_{present}(t) \\ &\quad + r_2\cdot\eta_2\cdot D_{global}) \end{aligned} \tag{7}$$

where $N_{next} \in allowP*_{i+1}$ and $allowP*_{i+1}$ is the feasible points set for ant k to choose the next point in plane P_{i+1}; η_1, η_2 are random numbers between 0 and 1; r_1,r_2 are learning rates; $D_{present}(t)$, $D_{global}(t)$ are path length functions that are improved based on the PSO algorithm to make the whole path length be as short as possible; $S(t)$ represent the safety grade of the feasible point $N_{next} \in allowP*_{i+1}$.

The calculation formula of $S(t)$ is given as follows:

$$S(t)=\begin{cases} 0 & (if \quad N_{next} \quad is \quad feasible) \\ 1 & (else) \end{cases} \tag{8}$$

where 1 represents that the point N_{next} is feasible and $N_{next} \in allowP*_{i+1}$; 0 represents that the point N_{next} is obstacle point.

The $D_{present}(t)$, $D_{global}(t)$ are very important factors in the heuristic function of improved ACO algorithm. The media of solution of velocity in PSO algorithm is introduced to construct the path length function. They are given as follows:

$$\begin{cases} D_{present}(t) = \frac{W}{D_{N_{now},N_{nextp}}+D_{N_{start},N_{nextp}}+D_{N_{nextp},N_{end}}} \\ D_{global}(t) = \frac{W}{D_{N_{now},N_{nextg}}+D_{N_{start},N_{nextg}}+D_{N_{nextg},N_{end}}} \end{cases} \tag{9}$$

where N_{nextp} is the optimal point searched by ant k in this iteration; N_{nextg} is the optimal point searched by all ants in last iteration; w is the weight value; $D_{N_{now},N_{nextp}}$ is the distance from point N_{now} to point N_{nextp}; $D_{N_{start},N_{nextp}}$ is the distance from point N_{start} to point N_{nextp}; $D_{N_{nextp},N_{end}}$ is the distance from point N_{nextp} to point N_{end}; $D_{N_{now},N_{nextg}}$ is the distance from point N_{now} to point N_{nextg}; $D_{N_{start},N_{nextg}}$ is the distance from point N_{start} to point N_{nextg}; $D_{N_{nextg},N_{end}}$ is the distance from point N_{nextg} to point N_{end}.

3.3 Pheromone update rule

Pheromone update consists of two parts that are local pheromone trail update and global pheromone trail update. The local pheromone trail is updated after the ant passes the point. The pheromone update can increase the probability of the point that the ant has not searched the goal of global search.

Before the pheromone is updated the ant k chooses the next point N_{next} in plane P_{i+1} firstly according to the selection probability function that is described as follows:

$$p^k_{N_{now},N_{next}}(t) = \frac{\sigma\tau^k_{N_{next}}(t)\cdot H^k_{N_{now},N_{next}}(t)}{\sum\limits_{N'_{next}\in allowP*_{i+1}} (\tau^k_{N'_{next}}(t)\cdot H^k_{N_{now},N'_{next}}(t))} \tag{10}$$

where σ is constant coefficient.

Table 1 Values of parameters of improved ACO algorithm based on PSO algorithm

Parameters	r_1	r_2	W	θ
Value	2	2	150	[−22°,22°]
Parameters	ϕ	ρ	ρ'	σ
Value	[−22°,22°]	0.5	0.2	1
Parameters	N_{start}	n_{start}	N_{end}	n_{end}
Value	(1,10,4)	(1 km,10 km,0.8 km)	(21,8,5)	(21 km,8 km,1 km)
Parameters	L_x	λ	ant number	iteration number
Value	1	(1 km,1 km, 0.2 km)	10	100

Then local pheromone trail update method is expressed as follows:

$$\tau^k_{N_{next}}(t)_{N_{next}\in allowP*_{i+1}} = (1-\rho)\tau^k_{N_{next}}(t) + \Delta\tau^k(t) \quad (11)$$

where ρ is the attenuation coefficient of pheromone of local trail; $\tau^k_{N_{next}}(t)$ is the pheromone value of the feasible point N_{next} and $\Delta\tau^k(t)$ is the pheromone released by the ant k that passed point N_{next}.

The global pheromone trail update method is expressed as follows:

$$f^k(t) = path^k_{N_{start},N_{end}} + \Delta\delta \quad (12)$$

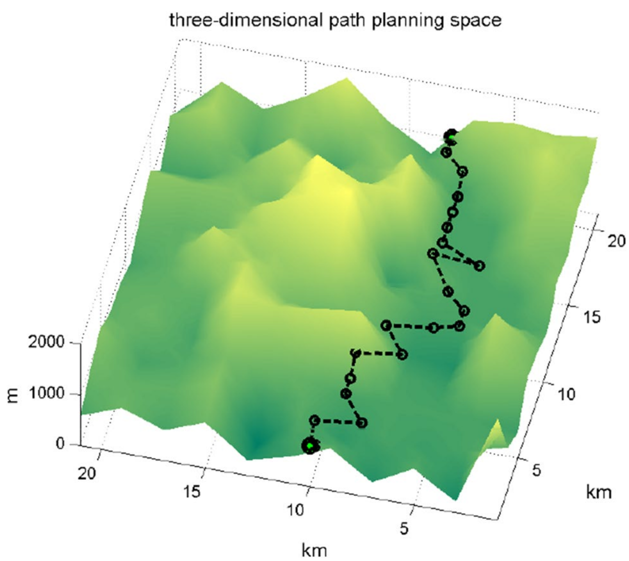

Fig. 5 Path planning with improved ACO algorithm

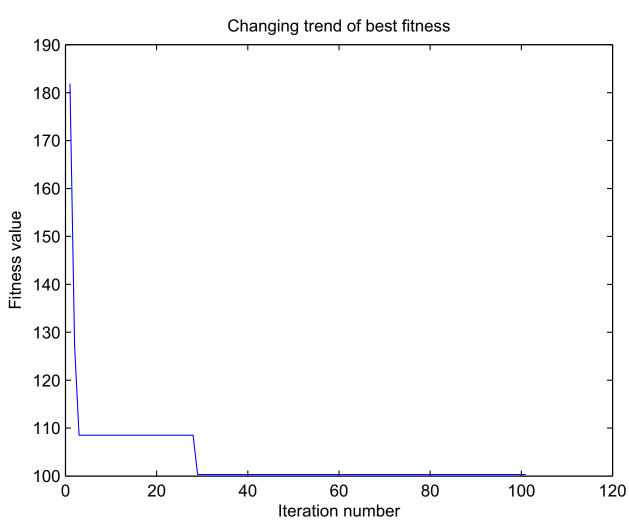

Fig. 6 Changing trend of best fitness with improved ACO algorithm

$$f_{best} = min(f^i) \quad (13)$$

$$\tau(t+1) = (1-\rho')\tau(t) + \frac{\rho'}{f_{best}(t)} \quad (14)$$

where f^k is the fitness value which indicates the cost of the ant k to construct its optimal path, $\Delta\delta$ is the limitation condition which is related with the ant k movements. ρ' is is the attenuation coefficient of pheromone of global trail.The global pheromone trail is updated after all ants have constructed their path.

3.4 Process design of algorithm

The solution of the three-dimensional path planning process is described as follows:

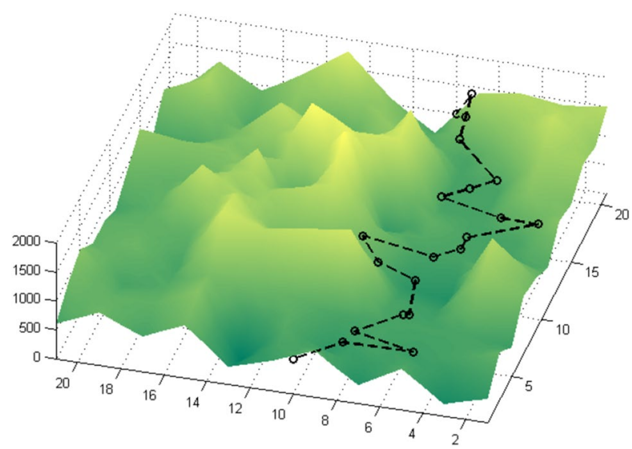

Fig. 7 Path planning with traditional ACO algorithm

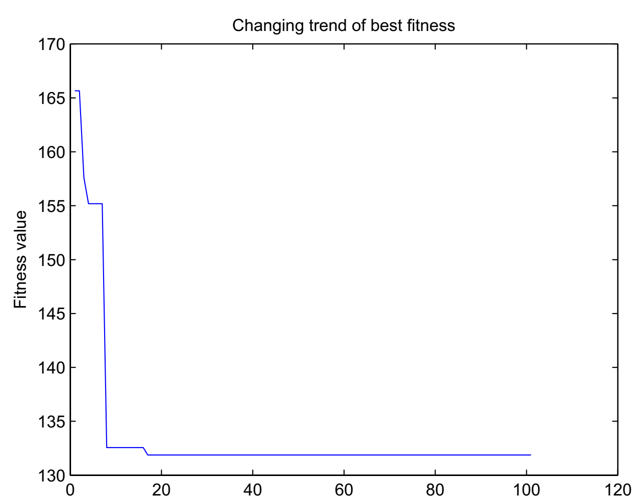

Fig. 8 Changing trend of best fitness with traditional ACO algorithm

Table 2 Comparison of path length (unit:km)

	1 time	2times	3 times	4 times	5 times	6 times	Average
Traditional ACO	37.09	38.53	43.63	39.11	34.78	36.86	38.33
Improved ACO	28.89	29.95	30.65	32.01	29.90	30.20	30.37

*Step 1*Start point and target point in abstract undersea environment model are determined firstly after that the three-dimensional undersea environment model has been built and the main direction of the ant movement is also determined.

*Step 2*On the basis of heuristic information and weight value of pheromone, the next point of the ants searching is determined according to Eq. (10).

*Step 3*Then local pheromone trail is updated according to Eq. (11).

*Step 4*We determine whether all the ants completed building a path. If they did not, then we return to *Step*2.

*Step 5*The global pheromone trail is updated according to equation (14) to determine whether the algorithm satisfies the stop condition and the optimal result output meets the conditions. Otherwise, we return to *Step*2.

4 Simulation results

The initial parameters values of the improved ACO algorithm are given in Table 1.

The performance of the improved ACO algorithm proposed in this paper applied in the three-dimensional path planning problems is shown in Figs. 5, 6. At the same time the performance of the traditional ACO algorithm is shown in Figs. 7, 8.

The experiment was conducted eight times. The planning path lengths of the ACO and improved ACO algorithms are shown in Table 2.

The simulation results show that the optimal path length is 28.8850*km* with the method in this paper and the optimal path length is 34.78*km* with the method of traditional ACO algorithm.The average path length with the method in this paper is significantly shorter than that with the method of traditional ACO algorithm. The path with the method of traditional ACO algorithm can fluctuate easily in the local depth,whereas the improved ACO algorithm based PSO algorithm performs better.

5 Conclusion

In this paper, the improved ACO algorithm is proposed to solve the path planning problem in three-dimensional complex undersea space for AUV. Firstly, the model of the three-dimensional undersea terrain space is established. Then the improve ACO algorithm is deduced to apply in the path planning in three-dimensional space underwater. The objective is to find the optimal path between the start point and target points under three-dimensional environment. The detailed process of the improved ACO algorithm is presented and the simulation of the comparison with the traditional ACO algorithm is shown that the algorithm proposed in this paper can improve search quality and accuracy. The output stability is better.

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