

Path Planning for Unmanned Underwater Vehicle Based on Improved Particle Swarm Optimization Method

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Abstract—Path planning of Unmanned Underwater Vehicle (UUV) is of considerable significance for the underwater navigation, the objective of the path planning is to find an optimal collision-free and the shortest trajectory from the start to the destination. In this paper, a new improved particle swarm optimization (IPSO) was proposed to process the global path planning in a static underwater environment for UUV. Firstly, the path planning principle for UUV was established, in which three cost functions, path length, exclusion potential field between the UUV and obstacle, and attraction potential field between UUV and destination, were considered and developed as an optimization objective. Then, on the basis of analysis traditional particle swarm optimization (PSO), the time-varying acceleration coefficients and slowly varying function were employed to improve performance of PSO, time-varying acceleration coefficients was utilized to balance the local optimum and global optimum, and slowly varying function was introduced into the updating formula of PSO to expand search space and maintain particle diversity. Finally, numerical simulations verify that, the proposed approach can fulfill path planning problems for UUV successfully.

Keywords—Unmanned Underwater Vehicle, path planning, PSO, time-varying acceleration coefficient, slowly varying function

1 Introduction

With the popularity and wide application of UUV (Unmanned Underwater Vehicle) in the ocean engineering and military operation fields, UUV as an indispensable intelligent navigation vehicle has attracted many attentions [1-4]. The path planning of UUV is one of the challenging problem in the application processing, because it is a foundation to ensure safe and efficient completion of complex underwater tasks [5-10]. The main objective of the path planning is considered as the computation an optimal

collision-free and the shortest trajectory from the start to the destination without hitting with any of the obstacles in underwater environment.

Generally, path planning problem can be classified into two categories: local path planning (LPP) and global path planning (GPP) [11,12]. LPP mainly relies on the unknown or partially known environmental information that is obtained from the acoustic sensors, such as forward-looking sonar. In dealing with the LPP problem, some approaches have been applied, such as artificial potential field method [13], fuzzy logic algorithm [14], and the rolling windows method [15]. However, those methods always exists some significant problems such as high computational cost, ineffective in path planning when the underwater space is large, and even deadlock phenomenon.

GPP as the other approach has been widely put forward, which can be formulated as a constrained optimization problem that is a non-deterministic polynomial hard problem with high computational complexity. Recent decades, numerous GPP approaches have been proposed such as diagrams algorithm and visibility graphs, especially global evolutionary algorithms [6,8,11,16-18]. The evolutionary algorithms compared with others GPP methods have advantages: easy implementation, strong capacity of global search, fast convergence rate and good robustness. Generally, there are some useful evolutionary algorithms [16] has been developed such as the heuristic A-star algorithm, genetic algorithm, ant colony algorithm, differential evolution, and obtained some great achievements.

Among those algorithm, PSO [6,16,19] as a global evolutionary algorithm is inspired by the behaviors of stochastic swarm such as flocks of birds and schools of fish, which mainly uses the swarm intelligent to achieve the goal of optimization. PSO has been applied to many domains with good performance such as system identification, neural networks and system control because of its characteristics of swarm intelligence, intrinsic parallelism, and inexpensive computational. However, Due to a few adjustable parameters such as population size, inertia weight and acceleration coefficients, PSO suffered from the premature convergence and trapping in local optimum problem, and even lack of population diversity. Several improved PSO algorithms, such as PSO-linearly inertia weight, PSO-fuzzy inertia weight and PSO-nonlinear inertia weight, had been proposed [8,19]. At present those methods have obtained with a certain performance improvement, but convergence and scarce exploration was also the frequent problems in the application process.

Inspired by the above discussion, a new particle swarm optimization algorithm (IPSO) is developed to solve global path planning for UUV in this paper. The remainder of this paper is organized as follow. The formulation and principle of global path planning for UUV is established in the Section 2, the UUV modeling and cost function are the research focus. The Particle swarm optimization is described briefly in the Section3. Improved PSO algorithm is presented by time-varying acceleration coefficients and slowly varying function in Section 4. Section 5 describes experimental simulation. Finally, conclusion of the study and future work in the paper are given in Section 6.

2 Formulation and Principle of Global Path Planning for UUV

The goal of path planning for UUV is to find an optimal collision free and the shortest trajectory path to avoid obstacles between the start and the destination with in an unknown underwater environment. To clear illustrate the path planning problem for UUV, this section presents formulation and principle of global path planning for UUV.

2.1 UUV Modeling and Environment Modeling

To clearly demonstrate path planning for UUV, UUV modeling and environmental modeling are developed by three assumptions, which are shown as following.

(1) UUV model is simplified as a particle description, and its kinematic model is demonstrated as:

$$\begin{cases} \dot{x} = v \cos \theta \\ \dot{y} = v \sin \theta \\ \dot{\theta} = \omega \end{cases} \quad (1)$$

where (x, y) denotes the position of the UUV. θ denotes the heading, and v denotes the velocity.

(2) The UUV system moves on a two-dimensional space, and the motion region can be expressed by finite convex polygons, in which there are finite number of unknown static obstacles. The UUV sensor system can determine the position of the obstacle by the perceived obstacle information and estimate the obstacle size, but limited scope of perception. The detection range of UUV sensor system is a circular area with radius r .

(3) The obstacle is depicted as the circle, which is subjected to a corresponding puffing process according to the actual dimensions and safety requirements of the UUV, that is, the radius of the obstacle includes its own radius and the radius of rotation of the UUV. Also, the obstacle boundary is a safe area.

2.2 Cost Function Modeling

It is very important to select a fitness function to evaluate the path individual. The tradition method of cost function generally considers the path length, which is shown as Fig.1.

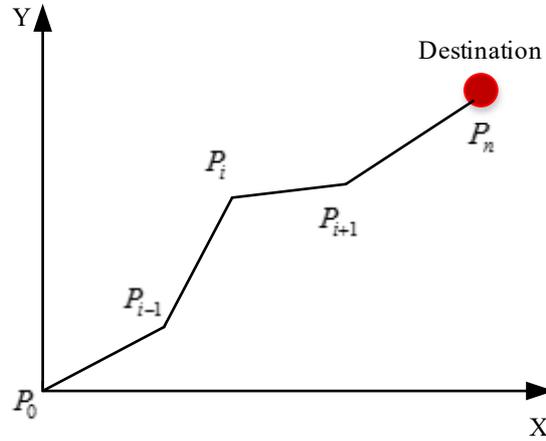


Fig. 1. Cost Function of Path Length

In Fig.1, $P_0(x_0, y_0)$ and $P_d(x_d, y_d)$ respectively denote the starting point and destination point coordinates for UUV planning, and $P_i(x_i, y_i)$ denotes i -th path point, $i = 1, 2, \dots, n$. To simplify the planning process, UUV searches the path point $P_i(x_i, y_i)$ by the fixed step length S . Thus, cost function can be calculated as follow

$$f_l = \sum_{i=0}^n L_{P_i} L_{P_{i+1}} \tag{2}$$

where $L_{P_i} L_{P_{i+1}}$ denotes the length between the point P_i and P_{i+1} .

According to the Eq.(2), the path planning of UUV can be converted to find the shortest path, however the constraint, whether the line between point P_i and P_{i+1} appear in the obstacles region, is not considered, which can only be judged by the algorithm itself and increased the complexity of algorithm design and computation.

In order to overcome the above shortcoming, we consider the attractive and repulsive fields as the other factors according to potential field theory, in which every search step onley need to find the best heading angle ψ [6].

(1). Cost function of repulsive potential field in avoiding obstacle. In underwater environment, there exists some static obstacle, which is shown as Fig.2.

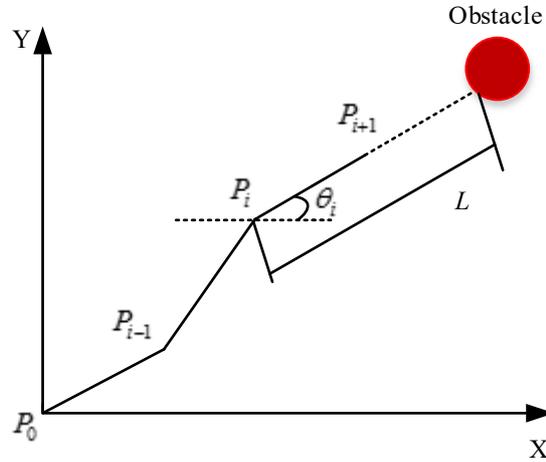


Fig. 2. Cost Function of repulsive Potential Field

In Fig.2, P_i denotes the position at i -th point, P_{i+1} denotes the candidate position at $i+1$ point, and L denotes the distance between the i -th point and obstacle at the heading angle θ_i . So, the cost function of avoiding obstacle can be defined as

$$f_o = S/L(\theta_i) \quad (3)$$

where S denotes the step length. At the heading angle θ_i , if the distance between UUV and obstacle is larger, the cost function is greater, otherwise the cost function is smaller.

(2). Cost Function of attractive potential field to the destination. According to the potential field theory, there is an attractive potential field existing between the UUV and destination, so attraction potential field between them is shown as Fig.3.

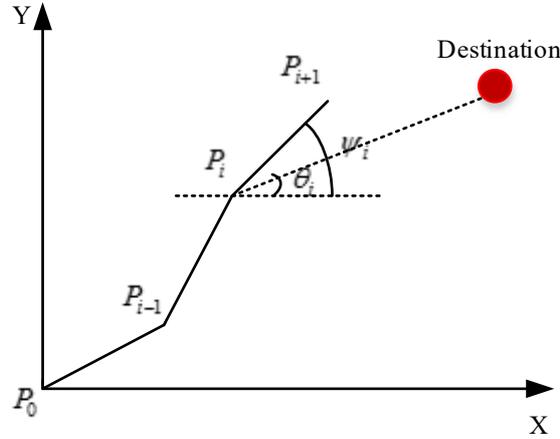


Fig. 3. Cost Function of attractive Potential Field

In Fig.3, θ_i denotes the angle between the current point P_i and the destination point P_d , and ψ_i denotes the heading angle between the candidate point P_{i+1} and destination point P_d . If attractive potential field obey the normal distribution, the cost function of attractive potential field to the destination can be defined as

$$f_d = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\psi-\theta)^2}{2\sigma^2}} \quad (4)$$

where σ is parameter of normal distribution.

Then, the cost function of attractive and repulsive fields can be calculated as

$$f_p = k_o f_o - k_d f_d, k_o > 0, k_d > 0 \quad (5)$$

where k_o and k_d are the weight coefficient.

Finally, according to the Eq.(2)and Eq.(5), total cost function of the path planning for UUV can be calculated as

$$f = w_l f_l + w_p f_p, w_l > 0, w_p > 0 \quad (6)$$

where w_l and w_p are the weight coefficient.

Based on the above analysis, the cost function of path planning at the current path point is established for UUV, the IPSO is used to search the trajectory of the cost function that obtains the minimum value of path point. And searched point can be taken as optimal path point at the next navigation path.

3 Improved PSO algorithm

In PSO, there exists two questions falling into local minima and lack of diversity of particles in practical application. How to solve the questions has attracted some attention. Therefore, we propose a novel Improved PSO (IPSO) with the purpose of increasing performance in this paper. In IPSO, time-varying acceleration coefficients and slowly varying function were employed, time-varying acceleration coefficients is utilized to balance the local optimum and global optimum, and slowly varying function is introduced into the updating formula of PSO to expand search space and maintain particle diversity.

3.1 Time-Varying Acceleration Coefficients

Acceleration coefficients determines the cognitive experience of particle and social experience of all particle in the search of swarm trajectory. That is, the larger c_1 is, the more is the attraction of particle toward its own personal best, therefore the more explorative capability. In contrast, the larger c_2 is, the more is the attraction of particles toward swarm global best, therefore the more exploitative capability. Therefore, the appropriate balance of the control learning factors c_1 and c_2 is very important to find the optimal solution accurately and efficiently.

Ideally, at the early stages of the optimization processing, particles should be focus more on exploration of region of search space in hope of finding the region included global optimum. And at the later of the optimization processing, particles should be focus more on exploitative and converge towards the global optimum. Therefore, to meet the requirement of ideal acceleration coefficients, c_1 and c_2 are updated in a way that the cognitive part is reduced and social part is increased along iteration process. So, a new time-varying acceleration coefficients is employed to enhance exploration and exploitation of particle towards optimal solution, which are defined as [20,21]

$$c_1 = c_{1,ini} + \frac{(c_{1,fin} - c_{1,ini})}{K} k \quad (11)$$

$$c_2 = c_{2,ini} + \frac{(c_{2,fin} - c_{2,ini})}{K} k \quad (12)$$

$$c_3 = c_1 \times (1 - e^{(-c_2 \times k)}) \quad (13)$$

where $c_{1,ini}$ and $c_{2,ini}$ are the initial values of cognitive factor and social factor respectively, $c_{1,fin}$ and $c_{2,fin}$ are the final values of cognitive factor and social factor respectively. c_3 as the adding part in Eq.(7) is utilized to converge to a better solution due to the fact that C_{best}^k the best solution in the k iteration. Therefore, the velocity and position of the particles are updated as:

$$V_{iD}^{k+1} = wV_{iD}^k + c_1r_1(P_{best}^k - x_{iD}^k) + c_2r_2(G_{best}^k - x_{iD}^k) + c_3r_3(C_{best}^k - x_{iD}^k) \quad (14)$$

$$x_{iD}^{k+1} = x_{iD}^k + V_{iD}^{k+1} \quad (15)$$

where r_3 is a random number in the interval of [0,1], similar to the r_1 and r_2 .

3.2 Maintain particle diversity based on Slowly-Varying Function

In order to maintain swarm diversity of and expand search space, slowly-varying function is introduced into the updating formula of PSO algorithm [19,22].

Definition1: Given function $l(x)$, $\forall \delta > 0$ and $a > 0$, there exists $l(x) > 0$ in $[a, +\infty)$, if $x^\delta l(x)$ is monotone increasing and $x^{-\delta} l(x)$ is monotone decreasing, then $l(x)$ is called as the slowly varying function(SVF).

Definition2: Given SVF $l(x)$, $\forall \delta > 0$ and $a > 0$, in $[a, +\infty)$, $x^\delta l(x)$ is defined as regular varying function (RVF).

RVF is employed to use in early-stage in PSO optimization because of the fact that PSO need better global optimization ability in the early-stage. The update formulates are calculated as

$$V_{iD}^{k+1} = wV_{iD}^k + c_1r_1(P_{best}^k - x_{iD}^k) + c_2r_2(G_{best}^k - x_{iD}^k) + c_3r_3(C_{best}^k - x_{iD}^k) \quad (16)$$

$$x_{iD}^{k+1} = x_{iD}^k + V_{iD}^{k+1} + x^\delta l(x) \quad (17)$$

where δ is the control parameter.

SVF is employed to use in later-stage in PSO optimization because of the fact that algorithm needs precise local searching ability. The update formulates are calculated as

$$V_{iD}^{k+1} = wV_{iD}^k + c_1r_1(P_{best}^k - x_{iD}^k) + c_2r_2(G_{best}^k - x_{iD}^k) + c_3r_3(C_{best}^k - x_{iD}^k) \quad (18)$$

$$x_{iD}^{k+1} = x_{iD}^k + V_{iD}^{k+1} + l(x) \quad (19)$$

SVF had been proved convergence. So, in this paper, we select a slowly varying function with increasing speed and disturbance relatively faster, it is shown as [19]

$$l(x) = (10 \ln x)^\gamma \quad (20)$$

where γ is the control factor.

3.3 Algorithm description

Based on the above analysis and discussion, solution procedures of the proposed method are summarized as follows:

Step1: Initialize the related parameters such as the size of the population M , learning factors $c1$, $c2$ and $c3$, maximum number of iterations K . initial values of cognitive coefficient $c1,ini$ and $c2,ini$, final values of cognitive coefficient $c1,fin$, and $c2,fin$.

Step2: Initialize the particles' velocities $V0$ and positions $X0$. optimal solution of individual particle $Pbest(0)$ and particle population optimal solution $Gbest(0)$, and particle best solution iteration $Cbest(0)$.

Step3: At $k=K$, calculate time-varying acceleration coefficients $c1$, $c2$ and $c3$ according to Eq.(11)- Eq.(13).

Step4: Calculate nonlinear inertia weight according to Eq.(10). If nonlinear inertia weight is equal to the 0.5, then turn to Step5, and If nonlinear inertia weight is smaller than 0,5, then turn to Step6, other then turn to Step7.

Step5: Update particles' velocities Vk and positions Xk according to Eq.(14)-(15), then turn to Step8.

Step6: Update particles velocities Vk and positions Xk based on regular varying function according to Eq.(16)-(17), then turn to Step8.

Step7: Update particles velocities Vk and positions Xk based on slowly varying function according to Eq.(18)-(19), then turn to Step8.

Step8: calculate cost function f in Eq.(6), and update the optimal solution of individual particle $Pbest$, particle population optimal solution $Gbest$, and particle best solution in the k iteration $Cbest$.

Step9: If the termination criterion is satisfied, export result of the algorithm, and iteration is equal to maximum number K , stop the algorithm. Otherwise, $k=k+1$, go back to Step3.

4 Simulation Experiment Analysis

To verify the correctness and validity of the proposed IPSO for UUV path planning, a representative scenario simulation is implemented in this paper. Assume that the UUV avoids underwater static obstacles to reach the destination. Simulation environment is a $10000(m) \times 10000(m)$ underwater space, there have eight randomly obstacles in space, which is described as circular area ($A\#,B\#,C\#,D\#,E\#,F\#,G\#,H\#$), and the location and radius are described as Table 1. Moreover, the size of the UUV is a circle, movement velocity is set as 2.5 m/s, the initial heading is set as $\theta = 45^\circ$, and the sensor ranger is set as 1000 m, the starting and destination are located at $(0,0)$ and $(10000,10000)$, respectively. The IPSO parameters are setting as population $M=200$, maximum number of iterations $K=200$, maximum weight $w_{max} = 10$ and minimum weight $w_{min} = 1$. The simulation experiment is designed by using the MATLAB on PC computer, and the configuration is Intel(R) Core™ i7 CPU3.40GHz, 8.0G RAM memory. The path planning trajectory of IPSO and PSO is shown as Fig.5-Fig.6.

As shown in Fig.5-Fig.6, the path planning of the proposed IPSO can avoid the static underwater obstacles successfully from the start to the destination, and the path is much smoother compared with PSO. That is because that the IPSO can converge faster to the global optimum and avoid falling into local optimum in the iterative process. In order to verify the better performance of the proposed method in path planning for UUV, the experiment is testified by Monte Carlo simulation of 100 times by the performance indicators: path length and run time under the same condition. The statistical results quantitative indicators of IPSO and PSO are shown in Table 2.

Table 1. The location and radius of obstacles

Obstacle	Location	Radius	Obstacle	Location	Radius
A#	(3250,3500)	900	E#	(5500,2000)	900
B#	(2300,900)	600	F#	(5200,6600)	1300
C#	(1800,7500)	1200	G#	(7000,5000)	800
D#	(8000,7600)	600	H#	(8500,2540)	800

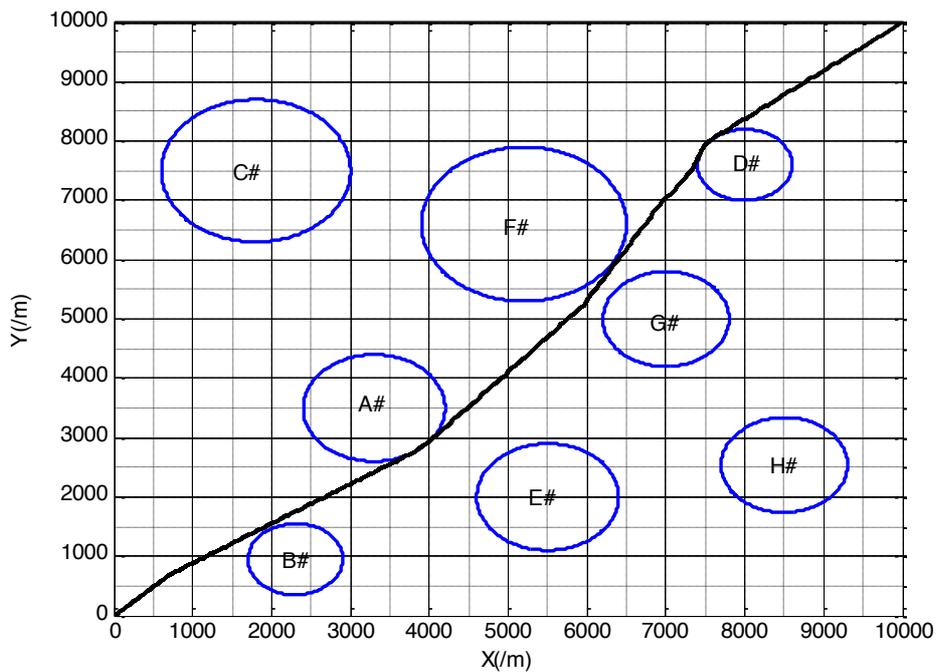


Fig. 4. Path planning trajectory of IPSO

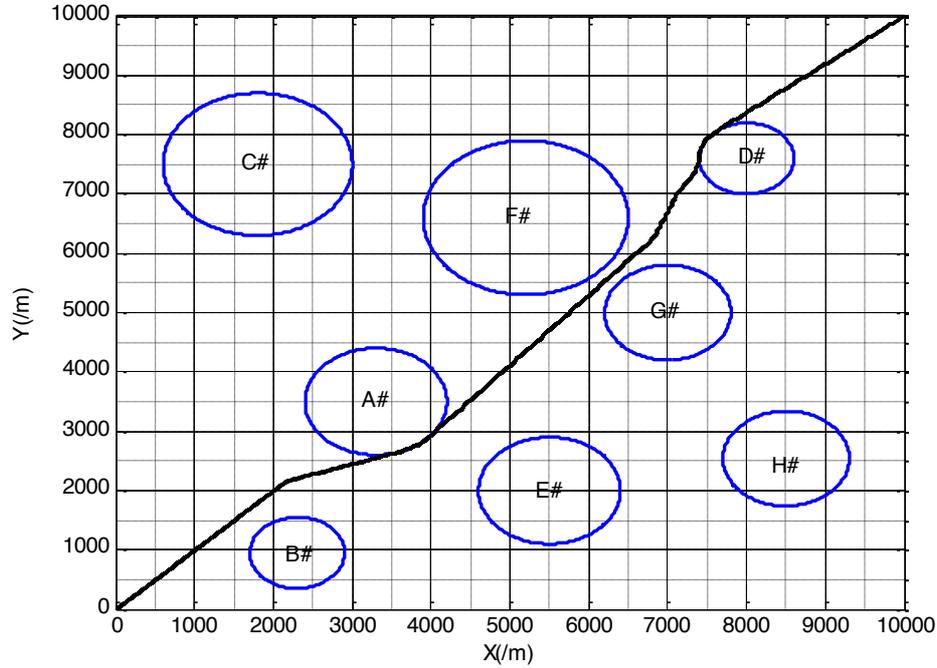


Fig. 5. Path planning trajectory of PSO

Table 2. Comparison results on path length and run time

Methods	Path Length	Run Time
PSO	16142(m)	6456.8(s)
IPSO	14980(m)	5992.0(s)

As can be seen from Table 2, it is reported that path length and run time with our proposed method reduces respectively by all 7.2% compared with PSO under the same simulation condition. Obviously, the proposed IPSO has a better performance in path planning for UUV.

5 Conclusions and Future Work

The path planning of UUV is one of challenging problem, because it is a foundation to ensure safe and efficient completion of underwater complex tasks. In this paper, a new improved particle swarm optimization (IPSO) is proposed to find a collision-free and the shortest path from a start to a destination without hitting with any of the obstacle. There are several contributions in this method as follows: (1) path planning principle for UUV is established, in which three cost functions, path length, attractive and repulsive fields are developed as an optimization objective. And (2) time-varying acceleration coefficients and slowly varying function are employed to improve

performance of IPSO. To verify the feasibility and effectiveness of proposed method, compared experiment has been established. Simulation results demonstrate that the IPSO can effectively fulfill path planning for UUV. Our future work will focus on the exact application of our proposed method in re-planning and navigation controller design, and multiple UUV formation coordinated control is also another hot issue in this field.

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