Local Path Planning Method of Unmanned Ship Based on Improved Firefly Algorithm

Kai Feng, Xiaoyuan Wang, Junyan Han, Shijie Liu

Abstract—**Local path optimization is an important guarantee for unmanned ships to maintain navigation safety at all times. The traditional firefly algorithm is slows convergence or drops into local optimum easily near obstacles for local path planning. And on this basic, a local path planning method for unmanned ship in clutter environment based on improved firefly algorithm was proposed in this paper. Based on the relationship between fireflies' distance and attractiveness, the initial range of fireflies is limited, and the position update formula is improved in this method. The simulation results show that the length of the local path is shorted effectively, the convergence speed is improved and local optimum can be avoided baesd the method. Therefore, the proposed method is reflected the good environmental adaptability and good path planning performance. It can provide new theoretical basis for the research of local path planning of unmanned ship.**

Index Terms **—Firefly algorithm; Unmanned ship; Ship collision avoidance; Path planning;**

I. INTRODUCTION

With the rapid development of the shipping industry, intelligent and unmanned ships have also emerged. Path planning has always been an important research topic in the field of intelligent unmanned ships, which can reflect the intelligent level of unmanned ships to some extent, and it is also an important prerequisite to ensure the safety of ship navigation at the same time. Therefore, it is of great practical significance to deeply study the local path planning method of unmanned ships, which can provide decision-making basis for autonomous navigation of unmanned ships, and improve the safety and economy of ship navigation.

On the research of ship path planning, Tang Pingpeng et al [1] constructed a grid model by rasterizing electronic charts, and proposed an automatic path generation method based on genetic algorithm under multi-objective constraints. Wang Yanlong et al [2] presented a path planning method, an S-57 electronic chart was used to establish an octree grid environment model and an improved A* algorithm was introduced to implement path planning. Liu Jian [3] designed a potential field dynamic grid method, which was combining the improved potential field method with the dynamic grid method. The environment model was established by dynamically refining the grid, and the improved potential field method was used to search for the optimal path. This method has fast convergence speed and can avoid the traditional potential field method from easily falling into the local minimum problem.

On the research of firefly algorithm (FA), A.K.Sadhu et al [4] presented and analyzed the arm path planning of robot, which was based on the Q-Learnning method, and FA was improved by adjusting the two intrinsic coefficients of algorithm when exploring the optimal solution in space. Liu et al [5] in order to solve the path planning problem of underwater robots, an autonomous navigation strategy was introduced to avoid invalid paths. And the authors improved the randomization parameters and light absorption coefficients of FA to avoid the algorithm falling into a local optimum. Liu Changping et al [6] introduced chaotic variables generated by logical self-mapping functions into the firefly algorithm, and chaotic sequences was used to optimize chaos for elite individuals. The convergence speed and optimization accuracy are improved effectively.

II. THE METHODS

A. *The formula of initial position*

Firefly individuals have their own search range. Path search requires that there are individuals with greater brightness in the search range. If there are no brighter individuals in the search range, the firefly moves randomly. Therefore, firefly can find the optimal solution by iterating on the position of the brightness difference. In the traditional firefly algorithm, firefly positions are randomly generated. Due to the randomness of the firefly position update, there will be a phenomenon that where fireflies are on obstacles at the initial moment, which only affects the effectiveness of path planning, but will affect the safety of unmanned ship. Therefore, it is necessary to limit the scope of random initialization of fireflies, and in order to prevent fireflies from being scattered on obstacles during initialization and to limit the range of fireflies, the coordinates of the fireflies that are initialized are defined as:

$$x_n = rand \cdot l + l \cdot cos\left(\frac{3}{2}\pi\right) \tag{1}$$

$$y_n = rand \cdot l + l \cdot sin\left(\frac{3}{2}\pi\right) \tag{2}$$

Where, $rand$ is randomization parameter and the l is fireflies' moving step in search space.

B. *The formula of position update*

In the search space, the firefly algorithm randomly initializes a group of fireflies $x_1, x_2, \cdots, x_n$, here, n is the number of fireflies, x_i represented the position of firefliy i in search space, which is also represented a potential solution. In order to obtain a new solution, the algorithm needs to update the position of the firefly every time iteration is completed. The magnitude of absolute brightness determines the pros and cons of solution, namely after the iteration is completed, fireflies will gathered around the fireflies with absolute brightness, and the optimal solution is obtained. When the distance between two fireflies is large, the attraction has a small effect on the update of the firefly position. Meanwhile, fireflies can use their own search capabilities to search the path, which will accelerate the convergence of the algorithm speed. However, when the distance between the two fireflies is small, the effect of attraction on the location update of fireflies becomes larger. If the search ability of the fireflies itself is greater than the effect of attraction, it will cause large fluctuations in the path of fireflies. In order to make the attraction dominate the firefly position update process and limit the random movement of the firefly itself, the position update formula was improved in this paper.

$$x_n(i+1) = x_n(i+1)\cdot(1-\beta_{ij}\cdot r_{ij}) + r_{ij}\left[x_n(i)\cdot\beta_{ij} + \alpha\cdot\left(rand-\frac{1}{2}\right)\right] \tag{3}$$

$$y_n(i+1) = y_n(i+1)\cdot(1-\beta_{ij}\cdot r_{ij}) + r_{ij}\left[y_n(i)\cdot\beta_{ij} + \alpha\cdot\left(rand-\frac{1}{2}\right)\right] \tag{4}$$

Where, $x_n(i+1)$ and $y_n(i+1)$ represented position coordinates of firefly at the next moment, $x_n(i)$ and $y_n(i)$ represented position coordinates of firefly at the present. β_{ij} is the attractiveness between two fireflies, r_{ij} is the distance between two fireflies , $rand$ is randomization parameter and $\alpha \in [0,1]$.

After adopting the new position update formula, the attraction has a small effect on the update of the fireflies' positions when the distance between fireflies is far, and fireflies can move freely according to their own search behavior. When the distance between fireflies is close, the attractive force has a greater effect on the update of the firefly's position, and the moving range of the fireflies themselves will decrease with the decrease of r_{ij}, so that they will move to fireflies with high absolute brightness under the action of gravity.

C. *Fitness function*

When there are obstacles around the ship, the movements of fireflies are used to find the optimal path. First, the path planning is transformed into the shortest path, and the distance between the firefly and the target point and the obstacle is used as a parameter of the FA fitness function. The global brightest firefly is located in each iteration and the ship will sailing to that position. The path planning problem includes collision avoidance and target search behaviors.The fitness function is defined as:

$$F_i = \frac{k_1}{D_{nob}{}^2} + k_2\cdot D_{nt}{}^2 \tag{5}$$

Where, k_1 represented the coefficient of collision, k_2 represented the coefficient of shortest path, D_{nob} represented the distance between the best firefly and the nearest obstacle, D_{nt} represented the distance between the target point and the firefly.

III. RESULTS AND DISCUSSION

In this paper, MATLAB (R2018) was used to simulate the effectiveness of the improved firefly algorithm in local path planning of unmanned ships. The configuration of the simulation computer is: Intel (R) i7-8700CPU (3.2GHz), 16GB RAM, 512SSD, WIN10 (64-bit).

In order to simplify the calculation, the location of obstacles in the collision avoidance environment and the maximum amount of fireflies were considered. In addition, trial and error was used to select simulation parameters. The algorithm parameters are shown in Table.I.

Table.I The values of simulation parameter

Simulation parameters	Values
The number of fireflies n	100
Iterations gen	100
The coefficient of collision k_1	1
The coefficient of shortest path k_2	0.01
The fireflies' moving step l	0.1
The light absorption coefficient γ	0.5
The mximum attractiveness at the light source β_0	0.5
The parameter α	0.5
The current position of ship $start$	[0,0]
The targett position of ship $target$	[50,50]

Assume that the unmanned ship's navigation range was a 50*50 area, and a number of obstacles were setted in the area. The values of the algorithm parameters are shown in Table.I. The traditional algorithm and improved algorithm were simulated and verified in different environments. The simulation results are shown in Fig.3 and Fig.4. The solid lines in Fig.3 and Fig.4 indicate the navigation path of the ship in this environment. The dark circles represented the obstacles in the navigation area. The starting point and target point were represented by circles and pentagrams respectively.

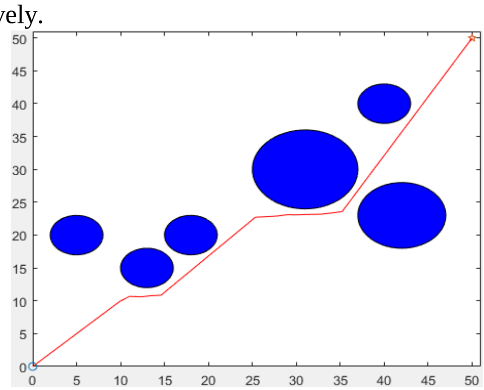

Fig.3 Simulation results (environment 1)

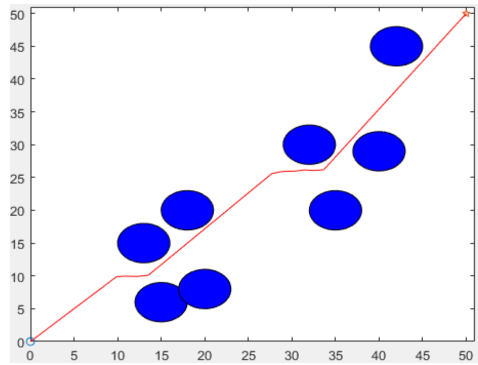

Fig.4 Simulation results (environment 2)

It can be seen from the experimental simulation results that the improved algorithm can effectively limit the local extreme value problems of firefly individuals near obstacles in different navigation environments. And the improved algorithm can be avoided obstacles stably and accurately.

In order to further verify the reliability and superiority of the improved algorithm, other algorithm in path planning was analyzed. In the field of swarm intelligence algorithm, genetic algorithm is the most representative algorithm, and it has many similarities with the firefly algorithm. Firstly, they are both random search algorithms based on swarm intelligence and introduce random factors in the optimization process. Secondly, they are both based on the individual's fitness information for optimization. Therefore, the improved firefly algorithm and genetic algorithm were compared and analyzed in this paper.

In the comparative simulation experiment, the starting point coordinates of the ship were $(0,30)$, and the ending point coordinates were $(30,0)$. The parameter of improved firefly algorithm settings are shown in Table.I, and the parameter of genetic algorithm settings are shown in Table II. The simulation results are shown in Fig.5 and Fig.6, and the comparison simulation results of the path length are shown in Table.III.

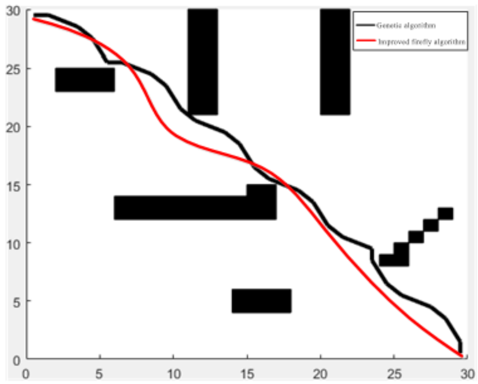

Fig.5 Comparison of simulation results (environment 1)

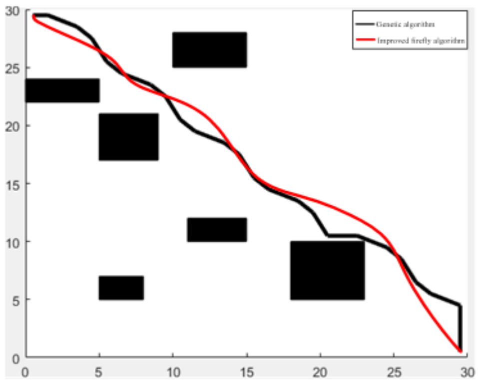

Fig.6 Comparison of simulation results (environment 2)

Table.III Comparison simulation results of path length

Algorithm	Path length (environment 1)	Path length (environment 2)
Improved firefly algorithm	52.27	55.64
Genetic algorithm	64.36	68.87

Through the above comparative simulations experiment, it can be seen that the path planning algorithm proposed in this paper can accurately reach the target point, which can shorten the path length compared with the genetic algorithm, and it can also planning a safe and reliable path for unmanned ship in environments with different obstacle distribution.

In conclusion, the traditional firefly algorithm was improved in this paper, and an unmanned ship local path planning model based on the improved firefly algorithm was established. The model takes into account the principles of ship's navigation efficiency and safety to realize the unmanned ship local path planning. Firstly, the path search behavior of firefly was analyzed and it was divided into collision avoidance behavior and target search behavior to ensure that the unmanned ship does not collide with obstacles and can reach the target point. Secondly, in view of the problem that the randomly generated points of fireflies may overlap with obstacles in the drone environment the initial position of fireflies was limited. Thirdly, in order to limit the random movement of the fireflies and make the attraction dominant in the process of updating the firefly position, the relationship between the attraction and distance of fireflies with different brightness and formulas for the position update were redefined in this paper. Finally, the feasibility and superiority of the improved algorithm were obtained through simulation verification and comparative analysis.

IV. Conclusion

In this paper, the slow convergence and drops into local optimum easily near obstacles in the application of traditional firefly algorithm for local path planning were studied. The traditional algorithm was improved by limiting the initial position range of fireflies and a new position update formula which based on the relationship between the firefly distance and attraction was established. The simulation verification and comparative analysis show that the improved algorithm can effectively shorten the length of the local path and prevent the firefly individuals from falling into local extremes. It has good universality and robustness, and can provide theoretical basis for the path planning of unmanned ships.

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