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Improved Path Planning for Mobile Robot Based on Firefly Algorithm

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***Abstract*— Aiming at the disadvantage that (Firefly Algorithm) FA is easy to fall into local optimum, (Modified Firefly Algorithms) MFA is proposed. By controlling the step factor α, the algorithm improves the adaptive control of α, and the convergence speed of the algorithm by controlling the parameter β_0. The simulation results show that MFA has better accuracy for other algorithms. The robot path optimization using MFA is shorter than that using FA, which proves the effectiveness of MFA.**

***Index Terms*— MFA; Mobile robot; Self-adaption; Path planning**

I. Introduction

Navigation is the focus of mobile robot research. Both single robot and multi robots are in a moving working state. Navigation is the core of mobile robot technology research. Generally speaking, mobile robot navigation is the path planning of robot from the beginning to the end, so that the robot can reach the target point smoothly without any interference. According to the working environment of mobile robot, path navigation can be divided into global path planning and local path planning. Global path planning is to obtain the global action environment information and an optimized global path by using the algorithm. The common methods include natural space method[1], configuration space method[2], grid method[3], etc. Local path planning achieves path planning by acquiring local environment information, and its common methods are artificial potential field[4], genetic algorithm[5] and so on. In the field of robotics, scholars tend to use artificial intelligence algorithms with strong robustness and high parallelism to achieve great results in the path planning of mobile robots in recent years.

This paper discusses the use of FA in artificial intelligence algorithms for path planning. Xin-she Yang[6] proposed FA in 2008 based on the characteristics of fireflies and the behavior of mutual attraction. The similarities and differences between FA and Particle Swarm Optimization (PSO) are analyzed[7]. Xin-she Yang optimized the centralized typical multi-peak test function with PSO, Genetic Algorithm (GA) and FA respectively. The result proves that FA has higher precision and convergence speed. There are a large number of researches on FA and path planning research in the literatures: Hidalgo et al. used FA to complete navigation tasks such as path security and path smoothing in the case of static obstacles[8]. L Deng et al. combined artificial immune network algorithm and position tracking control method for multi-robots path planning, so that following robot can avoid obstacles and follow the host robot[9]. Sadhu et al. proposed a method of path planning for robotic arm using FA based on Q-learning. They implement Q-learning on FA to search for global optimum in search space[10]. Wang et al. proposed an "modified firefly algorithm" to realize the path planning of unmanned combat aircraft (UCAV). Let UCAV avoid dangerous areas in complex battlefield environments and minimize fuel costs during navigation[11]. Patle et al. used improved FA and probabilistic model to study robot navigation in dynamic environment[12]. Y Peng et al. studied a local obstacle avoidance method based on two-dimensional lidar to enable ground robots to perform various tasks accurately[13].

However, the FA has the characteristics of easy falling into local optimal solution, low precision and "premature". Based on the existing problems of FA, this paper proposes MFA which enhances the robustness of the algorithm in the application process.

II. Firefly algorithm

FA is a stochastic optimization algorithm based on the fire behavior of fireflies. In order to ensure the efficiency, practicability and simplicity of the algorithm, the luminescence and phototaxis of fireflies are idealized. During the operation of the algorithm, only the partner of the firefly's illuminance and phototaxis is searched for, and the firefly is moved to the brightest firefly in the neighborhood, and its position is constantly updated:

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The FA is based on the following three characteristics:

1) There is no gender distinction between fireflies and the attraction between two fireflies is only related to the brightness of each firefly;
2) The attraction between two fireflies is proportional to their brightness and inversely proportional to the distance between individuals. High-intensity fireflies move toward to the low-light fireflies and update their position. The brightness is determined by where they are located. If the firefly perches in a better position, it will emit brighter light and attract other fireflies. When the brightness of adjacent fireflies is the same, the fireflies move randomly.
3) The brightness of fireflies is determined by the value of the objective function to be optimized.

Definition 1: The maximum fluorescence brightness of firefly

$$I_0 = f\left(x_i\right) \tag{1}$$

In the formula(1), x_i is the spatial position of the first firefly, and $f(x_i)$ is the fitness value of the firefly's location.

Definition 2: Relative fluorescence brightness of fireflies

$$I = I_0 \mathrm{e}^{-\gamma \mathrm{r}_{ij}} \tag{2}$$

In the formula(2), γ is the light intensity absorption factor which is the influence coefficient of the propagation medium on the fluorescence brightness of fireflies. Generally, it is a constant, $\gamma \in [0, \infty]$, but in most of the actual problems, $\gamma \in [0.01, 100]$; r_{ij} is the Euclidean distance between fireflies i and j.

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{\mathrm{k}=1}^{d} \left(x_{i,k} - x_{j,k}\right)} \tag{3}$$

In the above formula(3) , d is the spatial dimension, $x_{i,k}$ is the k-th component of firefly i in the d-dimensional space. In the specific optimization problem, the fluorescence brightness of the firefly at position x is calculated.

Definition 3: attractiveness

$$\beta\left(r\right) = \beta_0 e^{-\gamma r_{ij}^{m}} \tag{4}$$

In the formula(4), β_0 is the maximum attraction, also called the source attraction($r = 0$); $m = 2$.

When the brightness of firefly j is higher than firefly i, firefly i is attracted to move and update its position.The updating formula for the position of firefly i is as follows:

$$x_i\left(t+1\right) = x_i\left(t\right) + \beta_0 e^{-\gamma r_{ij}^{m}} + \alpha \varepsilon_i \tag{5}$$

Among the formula(5), $x_i(t+1)$ is the position of x_i after the first movement; α is the step factor, and its value range is generally $[0, 1]$; ε_i is a random number vector generated by Gaussian distribution, uniform distribution or other distributions.

The basic flow of FA is shown in Fig.1.

III. Modified firefly algorithm

Although FA has the characteristics of fast convergence in global search and local search, it can find the optimal solution quickly, but the algorithm may fall into local optimum or "premature" phenomenon. The algorithm may not be able to search for global optimization later. In order to reduce the possibility of the algorithm falling into local optimum, this paper modifies the algorithm.By controlling the parameter α and β which affect this phenomenon, improve the optimization ability of the algorithm

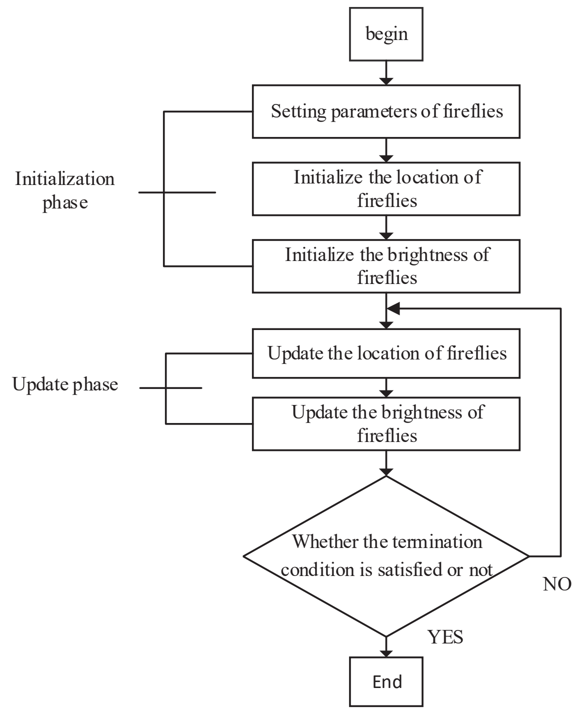

Fig. 1. A flow chart of FA

A. Adaptive control of step factor

In the initial stage, each firefly factor is optimized. Assuming that F_{best} and F_{worst} are the best and worst individuals after each firefly iteration. Four fireflies F_{n1},F_{n2},F_{n3},F_{n4} are randomly selected from the firefly population, and $n_1 \neq n_2 \neq n_3 \neq n_4$, then use them to generate two new body types.

Among them, λ is a random parameter. Generally, the values are taken in the interval $[0, 1]$. Then these fireflies are used to generate several new fireflies as shown below.

$$F_{new1} = F_{n1} + \lambda \times \left(F_{n2} - F_{n3}\right) + \lambda \times \left(F_{n3} - F_{n4}\right) \tag{6}$$

$$F_{new2} = F_{new1} + \lambda \times \left(F_{best} - F_{worst}\right) \tag{7}$$

$$F_1 = \begin{cases} F_{new1} & if \quad k_1 \leq k_2 \\ F_{best} & if \quad k_1 > k_2 \end{cases} \tag{8}$$

$$F_2 = \begin{cases} F_{new1} & if \quad k_3 \leq k_2 \\ F_j & if \quad k_3 > k_2 \end{cases} \tag{9}$$

$$F_3 = \begin{cases} F_{new1,j} & if \quad k_4 \leq k_3 \\ F_j & if \quad k_4 > k_3 \end{cases} \tag{10}$$

$$F_4 = F_{new1} \ if \ k_5 \leq k_4 \ or \ k_5 > k_4 \tag{11}$$

$$F_4 = \delta \times F_{worst} + \psi \times (F_{best} - F_{worst}) \tag{12}$$

k_1,k_2,k_3,k_4,σ,ψ are all random parameters. Their value range is generally [0,1]. All the fireflies generated above are calculated by the objective function. When the objective function value of the firefly i is greater than that of the best firefly, the firefly i will replace the original position of the best firefly.

The step factor α is used in the position update formula(7) to control the random search of the algorithm. When the adjacent fireflies do not search for these fireflies within a given range, their search range is controlled. The parameter α controls each firefly in random motion, and its range of values is generally within [0,1]. When the value of α is large, it will lead the firefly to search for the optimal solution in the global search space which will lead to a lower search speed. If not, the firefly will find the local optimal solution and fall into the "premature" state. Therefore, the value of step factor α affects the balance between global and local optimum.

In order to realize the adaptive control process of the random parameter parameter α, formula(13) is used to modify the parameter α and replace it with the update equation of the optimal positio to improve the ability of the improved algorithm to search locally and globally.

$$\alpha = \left(\frac{1}{2M_{\max}}\right)^{\frac{1}{M_{\max}}} \alpha^{Iter} \tag{13}$$

B. Search optimization

Iter is the iteration number of fireflies and M_{max} is the maximum iteration number. In the optimization process, the algorithm achieves the balance between local search and global search by changing the value of α.

β_0 is a constant in the original equation. Its value will not change during the whole process of the algorithm. Now we introduce a cyclic variable ρ to modify the parameter.

$$\beta_0 = \eta - \frac{1}{Maxlter}\rho \tag{14}$$

MaxIter is the maximum number of iterations. The modified β_0 is introduced into the mutual attraction equation as follows:

$$\beta(r) = \left(\eta - \frac{1}{MaxIter}\rho\right) e^{-\gamma r^2} \tag{15}$$

For controlling the search mode of the algorithm, the initial stage algorithm searches for the optimal value globally. In order to speed up the convergence speed of the algorithm, changing the value of β_0 will make the algorithm focus on local search in the final stage of the search which greatly improves the convergence speed of the algorithm. After controlling the parameters, the improved objective iteration formula is as follows:

$$X_{i+1} = X_i + \left(\eta - \frac{1}{MaxIter}\rho\right) e^{-\gamma_{ij}^2} + \left(\frac{1}{2G_{\max}}\right)^{\frac{1}{G_{\max}}} \xi^{Iter} \varepsilon_i \tag{16}$$

The Modified algorithm is superior to the FA in the balance and convergence speed of global search and local search.

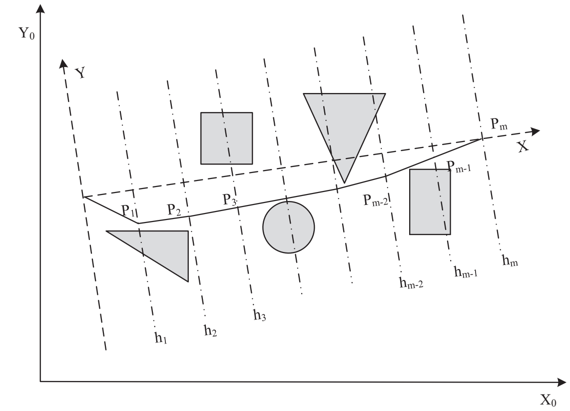

Fig. 2. Process path planning before adjustment

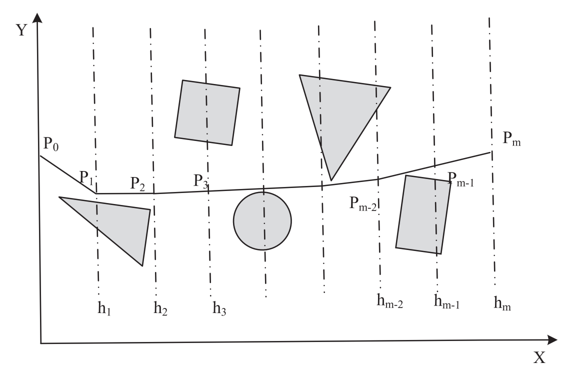

Fig. 3. Process path planning after adjustment

C. Path description

Path planning of robot is that the mobile robot reaches the target point through m+1 points from the starting point.. As shown in the Fig.2. The line connecting the starting point O and the end point P_m of the mobile robot is the X axis and the line passing the starting point O and perpendicular to the X axis is used as the Y to establish the global coordinate system O-XY. Then dividing the O_{P_m} into m segments, and making a vertical line through each halved point to obtain a vertical line(h_1,h_2,...,h_4). The intersection point of each vertical line with the path is the target point(P_1,P_1,...,P_{m-1}) that the part in the path must pass. Under the premise of not affecting the result, for reducing the calculation amount and facilitate observation, the X-axis is translated to extract a new coordinate system, and the path planning of the mobile robot is transformed into a series of target point selection processes.

In order to improve the timeliness of the robot, the total path of the robot from the starting point to the end point should be as short as possible, that is to say, the function S should be minimized.

$$S = \sum_{j=0}^{m} S_{P_j P_{j+1}} \tag{17}$$

$S_{P_j P_{j+1}}$ represents the distance from P_j to P_{j+1}, and can also be expressed as:

$$S = \sum_{j=0}^{m} \sqrt{\left(x_{P_j} - x_{P_{j+1}}\right)^2 + \left(y_{P_j} - y_{P_{j+1}}\right)^2} \tag{18}$$

IV. Performance Analysis of Algorithms

The performance of standard FA and MFA is validated by test function. The object selection of this paper is as follows binary non-linear objective function:

$$f(x, y) = \frac{\sin(x^2 + y^2)}{x^2 + y^2} \tag{19}$$

The three-dimensional graph of the binary nonlinear objective function is shown in the Fig.4.

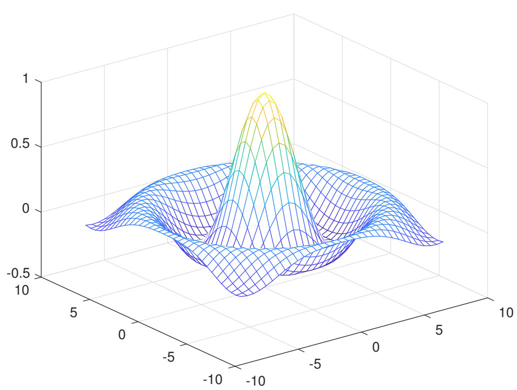

Fig. 4. Graphics of function $f(x, y)$

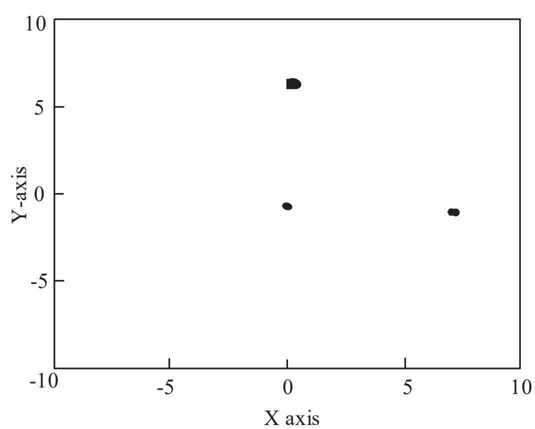

Fig. 5. The results of FA test nonlinear function diagram

As shown in the Fig.4, the function takes the maximum at (0,0) and there are several local extreme points near the maximum. The modified function is suitable for the optimization experiments of the two algorithms. The firefly algorithm and the improved firefly algorithm are used to optimize the objective function. The number of fireflies given at the beginning is 100, the number of iterations is 50, the light intensity absorption factor $\gamma = 0.5$, $\alpha = 0.2$, $\beta_0 = 1$. The optimal distribution results of the firefly algorithm and the improved firefly algorithm are obtained as shown in the Fig.5 and Fig.6.

From the above test results, we can see that most of the fireflies in the FA are at the local extremum point, only a few at the maximum extremum point. The fireflies in the MFA basically gather near the maximum point, which improves the problem that the standard firefly algorithm is easy to fall into the local optimum.

On the basis of the above simulation. By choosing the multi-peak function as the optimization object, many simulation experiments were carried out. The simulation results show that MFA has a great improvement in search ability and convergence speed.

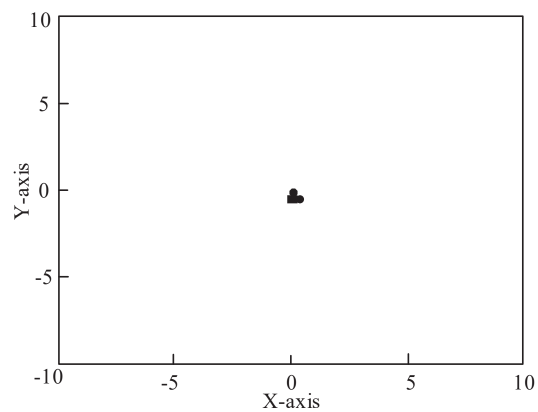

Fig. 6. The results of IFA test nonlinear function diagram

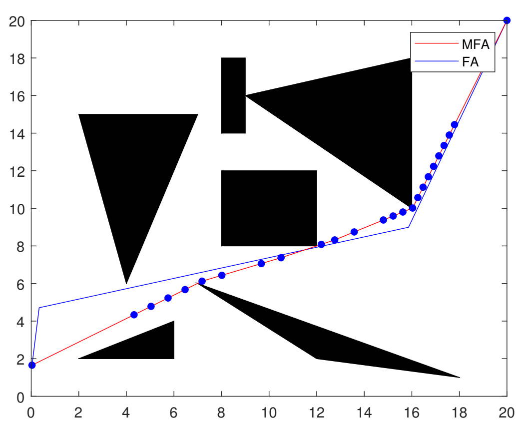

Fig. 7. Moving paths of FA and MFA

In order to verify the feasibility and effectiveness of MFA in robot path planning, the simulation was verified at MATLAB R2018a. A planar work environment is constructed on the experimental platform and placed in different obstacles.

TABLE I

PATH LENGTH OF THREE ALGORITHMS

Path \ Algorithm	GA	FA	MFA
Shortest path	29.83	29.58	28.46
Average path	31.19	30.84	29.82

Getting the optimization path of the robot in the cases of GA, FA and MFA.

The starting position of the robot is (0.3, 2.2) and the ending position is (20, 20). Fig.7 is the collision-free optimized path planned by the robot using FA and MFA. Fig.8 is a collision-free optimization path for robots using GA and MFA planning. Table 1 is a summary of data from 30 experiments using three algorithms. Compared with GA, MFA reduces 4.6% and 4.3% respectively in the optimal and average solution of searching path lengthand MFA decreased by 3.8% and 3.3% compared with FA.

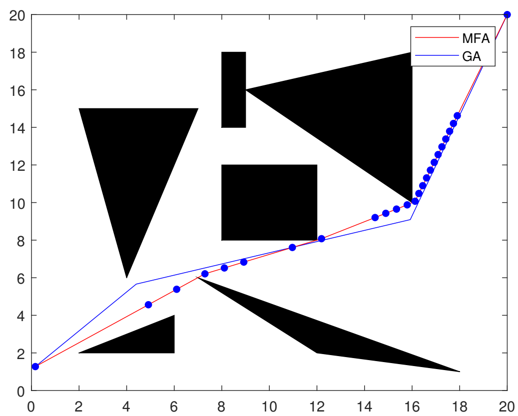

Fig. 8. Moving paths of GA and MFA

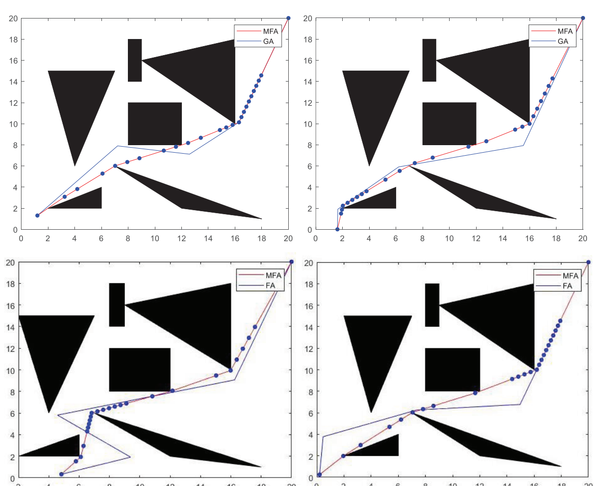

Fig. 9. Path optimization of four different starting points

For verifying the feasibility of the algorithm, three algorithms are used to optimize the path in the same obstacle and terminal, different starting point environment. As shown n the Fig.9, it can be seen that when the robot uses FA or MFA for path planning, the trajectory is discontinuous While using MFA for path planning, the moving trail of the robot is higher smoother, shorter path, better than FA and GA.

V. CONCLUSION

The MFA proposed in this paper solves the problem that FA is easy to fall into “premature and cannot achieve global optimality when searching for the optimal solution by adaptively controlling the step factor . The experimental results show that when using MFA for path planning, the robot’s trajectory length is shorter than FA and GA, which significantly improves the operational efficiency of mobile robot. It also laid the foundation for path planning research in an unknown environment.

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