Improved Artificial Potential Field Method Fused with Fuzzy Logic Algorithm

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Abstract: *The APF (artificial potential field, APF) has been applied to the path planner of mobile robots by many technology developers and engineers because of its simple structure, small amount of calculation, good obstacle avoidance effect. However, in complex environments, the robot using this algorithm will have target inaccessibility and local minimum. In this article, the Euclidean distance between the mobile robot and the target point is multiplied by the gain coefficient of the potential field function as a regulating factor, which is used to optimize the repulsive potential field function to avoid the situation that the repulsive force is greater than the attractive force near the target point and the target is unreachable. Furthermore, APF was coupled with fuzzy logic algorithm based on fuzzy logic algorithm (Improved Artificial Potential Field Method Fused with Fuzzy Logic Algorithm, FUZZY_APF). This method helps a mobile robot trapped in a local minimum to set a virtual target point nearby, providing it with an escape force to make the local minimum disappear. The FUZZY_APF proposed in this article will be simulated and tested by MATLAB software. The simulation results show that FUZZY_APF can help mobile robots that encounter local minima and unreachable goals in complex environments to complete path planning tasks. Compared with the algorithm without improvement, the path planned by the FUZZY_APF is smoother, and the planning time and the planning path are shorter.*

Keywords: *Improved artificial potential field method; Fuzzy logic algorithm; Virtual target point*

1. Introduction

With the further deepening of the contemporary scientific and technological revolution, mobile robot technology is also developing in a more intelligent direction, and its practical application has also penetrated all walks of life[1,2]. Path planning technolog[3-5] is the core of mobile robot obstacle avoidance function, which has always been the research direction of researchers from all over the world.

Path planning includes two directions: global path planning techniques applied to consistent static obstacle avoidance[6,7] and local path planning techniques applied to dynamic obstacle avoidance[8]. Global path planning technology is to plan a collision-free path for the mobile robot to reach the destination in advance when the environment information is known and the obstacles are static. Local path planning can be described as follows: the mobile robot collects the surrounding environment information in real-time through its own installed sensors and plans an obstacle-free path for itself according to the established local cost map. Local path planning includes dynamic window method, A-star algorithm that can be suitable for a variety of scenario, genetic algorithm with better global exploration ability, particle swarm optimization algorithm with better guidance for updating the position and velocity of the mobile robot, RRT algorithm for multidimensional space. Etc. However, these algorithms also have some obvious shortcomings. The mobile robot using the particle swarm optimization algorithm as the locally path planner agrees to fall into a local optimal solution in the process of planning a path. Genetic algorithm has weak local search ability and cannot obtain the optimal solution most of the time. The mobile robot using A-star as the local path planning technique has A poor effect on real-time obstacle avoidance when facing dynamic and unknown obstacles. The performance of RRT is easily influenced by the complexity of the mobile robot driving environment.

Local path planning also includes the APF, which has low computational complexity, simple structure, and good dynamic obstacle avoidance effect. However, the mobile robot applying this algorithm will encounter the local minimum and target unreachable in a complex environment. Many scholars and engineers have put forward optimization schemes. Yang et al. optimized the gravitational potential field function, and this method successfully solved the problem of unreachable targets. Feng et al. proposed to solve the local minimum in setting virtual obstacles; Duan et al. propose to set virtual target points to solve local minima. Luo et al. combine the APF with deep learning to optimize their defects; There are also many that couple the APF with other path planning algorithms to improve the performance of the APF algorithm when it encounters local minimum and target unreachable problems in path planning, such as A*, DWA, RRT, etc.

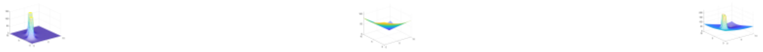
In this article, the Euclidean distance between the two-dimensional coordinates of the mobile robot and the two-dimensional coordinates of the destination is used as an adjustment parameter multiplied by the coefficient of the repulsion function of the APF to optimize the repulsion function, help the mobile robot to reach the destination smoothly, and make the phenomenon of the unreachable target disappear. On the basis of this scheme, the APF and fuzzy logic algorithm are coupled to help provide virtual target points when the mobile robot is trapped in a local minimum in a complex environment. The virtual target point will provide a release force to help the mobile robot escape from the state of the local minimum.

This article will consist of the following sections. In Section 2, we explain the APF and study why it gets stuck in local minimums and cannot reach the target. In Section 3, we explain how to make the Performance of APF better and give the theories behind it. Section 4 consists of experiments and discussions using simulations. In Section 5, The improved algorithm is discussed and analyzed. Lastly, Section 6 gives a short overview of the article and discusses possibilities for future research.

2. The Introduction of Principles and Disadvantages of APF

2.1 Introduction to The Principle of APF

In 1986, Khatib proposed a virtual force method for mobile robot path planning, namely the APF. The mobile robot is likened to a positive charge, then the target point is a negative charge in the potential field, and the obstacle is a positive charge in the potential field. They apply repulsive and attractive forces to the mobile robot in the potential field and decide the running route of the mobile robot. Figure 1 presents a three-dimensional view of the potential field.



(a) (b) (c)

Figure 1. This is a 3D model of the potential fields, they should be listed as:(a) a description of what is repulsive potential field model; (b) a description of what is gravitational potential field mode; (c) a description of what is a 3D model of the potential field.

The applied potential energy of the mobile robot in the potential field is inversely related to the Euclidean distance between the two-dimensional coordinates of the robot and the two-dimensional coordinates of the destination.

From Equation 1, the magnitude of the gravitational potential energy exerted by the mobile robot can be calculated.

$$U_{att}(X) = \frac{1}{2}\eta\rho^2(q_{rob}, q_{target}) \quad (1)$$

Where η is the repulsive potential field coefficient, q_{rob} is the two-dimensional coordinate of the mobile robot, q_{target} is the two-dimensional coordinate of the target point, and $\rho(q_{rob}, q_{target})$ is used as a vector with the size of the Euclidean distance between the two coordinates. The direction of the vector is q_{rob} pointing to q_{target}. The corresponding gravitation force F_{att} can be obtained by taking the partial derivative of equation 2.

$$F_{att} = -\nabla U_{att} = \eta\rho(q_{rob}, q_{target}) \tag{2}$$

The influence range generated by obstacles in the potential field can be set artificially, which is called a repulsive potential field. When the mobile robot does not enter the area affected by obstacles, the repulsive potential energy applied to the mobile robot is 0. On the contrary, when the mobile robot operates in the repulsive potential field created by the obstacle, the Euclidean distance between the two-dimensional coordinates of the obstacles and the two-dimensional coordinates of the mobile robot is inversely proportional to the repulsive potential energy value applied to the mobile robot. Equation 3 is used to derive the potential energy magnitude applied to the mobile robot by the repulsive potential field.

$$U_{req}(X) = \begin{cases} \frac{1}{2}k\left(\frac{1}{\rho(q_{rob}, q_{obstacle})} - \frac{1}{\rho_{obstacle}}\right)^2 & 0 \le \rho(q_{rob}, q_{obstacle}) \le \rho_o \\ 0 & \rho(q_{rob}, q_{obstacle}) \ge \rho_o \end{cases} \tag{3}$$

k is defined as the gain coefficient, and the specific value can be set independently according to the actual situation. q_{rob} is the mobile robot coordinate, $q_{obstacle}$ is the obstacle coordinate $\rho(q_{rob}, q_{obstacle})$is a vector whose direction is q_{rob} pointing to $q_{obstacle}$ and magnitude is the Euclidean distance between q_{rob} and $q_{obstacle}$. ρ_o is defined as a fixed value that represents the maximum distance that an obstacle can affect. The magnitude of the repulsive force exerted by the mobile robot can be obtained by taking the partial derivative of Equation 3, and the mathematical expression is Equation 4

$$F_{req}(X) = \begin{cases} k\left(\frac{1}{\rho(q_{rob}, q_{obstacle})} - \frac{1}{\rho_{obstacle}}\right) \nabla(q_{rob}, q_{obstacle}) & 0 \le \rho(q_{rob}, q_{obstacle}) \le \rho_o \\ 0 & \rho(q_{rob}, q_{obstacle}) \ge \rho_o \end{cases} \tag{4}$$

Equation 5 is the mathematical model expression of the sum of the attractive force and repulsive force that the mobile robot is subjected to in the potential field.

$$F = F_{att} + \sum_{0}^{X} F_{req}(X) \tag{5}$$

The coordinates of the next operation of the mobile robot can be derived from Equation 6.

$$\begin{cases} x_{next} = x + \rho\frac{F_X}{|F_X|} \\ y_{next} = y + \rho\frac{F_Y}{|F_Y|} \end{cases} \tag{6}$$

The coordinates of the mobile robot are defined as (x, y), and the coordinates at the next moment are (x_{next}, y_{next}) driven by the repulsive and attractive forces calculated by Equations 2 and 4. The component force F_X and component force F_Y can be obtained by orthogonal decomposition of the resultant force found in Equation 5. ρ is the distance that the mobile robot moves each time.

2.2 Defect Cause Analysis of APF

The APF is beneficial for real-time control in mobile robotics due to its simple structure and practicality at the bottom layer. However, it does have some drawbacks, namely the presence of local minimums and challenges in reaching certain targets.

The occurrence of local minimums is attributed to complex obstacles encountered during the robot's movement, where the combined repulsive force from the obstacle in the path and the attractive force from the target point may result in a net force of less than or equal to zero, causing the robot's progress to be hindered. Refer to Figure 2 for a visual representation.

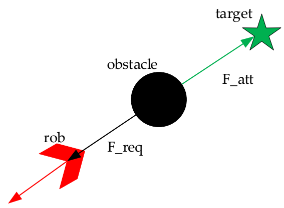


Figure 2. Force analysis of a mobile robot when it encounters local minima

Because there are complex obstacles near destination, the repulsive force exerted on the mobile robot is greater than or equal to the gravitational force, which makes the robot oscillate and drift near the destination and cannot complete the path planning task. Figure 3 illustrates this scenario.

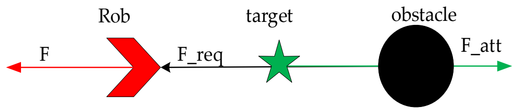


Figure 3. Schematic diagram of the reason for the unreachable goal.

The diagram reveals that both the inaccessibility of the target and the occurrence of local minimums stem from the net force of repulsion and attraction being less than or equal to 0, as demonstrated in equation 7.

$$F_{req} + F_{att} \leq 0 \tag{7}$$

3. Optimization of The APF

3.1 Improvement of The Gain Coefficient of The Repulsion Function

The Euclidean distance between the two-dimensional coordinates of the mobile robot and the two-dimensional coordinates of the end point is multiplied by the gain coefficient of the repulsive force function as an adjustment parameter, so that the repulsive force received by the mobile robot during operation becomes smaller as the distance between the two-dimensional coordinates becomes smaller. The optimized coefficient k is given in equation 8.

$$k_{imp} = k * \frac{\left(sqrt\left(\left(x_{target} - x_{rob}\right)^2 + (y_{target} - y_{rob})^2\right)\right)^n}{\left(sqrt\left(\left(x_{target} - x_{rob}\right)^2 + (y_{target} - y_{rob})^2\right) + 1\right)^n} \tag{8}$$

The optimized repulsion function gain coefficient is substituted into Equation 4 to complete the optimization of the repulsive function, and the optimized mathematical model is shown in Equation 9

$$F_{req}(X) = \begin{cases} k_{imp}\left(\frac{1}{\rho(q_{rob}, q_{obstacle})} - \frac{1}{\rho_{obstacle}}\right) \nabla\rho(q_{rob}, q_{obstacle}) & 0 \leq \rho(q_{rob}, q_{obstacle}) \leq \rho_o \\ 0 & \rho(q_{rob}, q_{obstacle}) \geq \rho_o \end{cases} \tag{9}$$

3.2 Improved Scheme Based on Fuzzy Logic Algorithm

Fuzzy logic algorithms are mainly used to deal with local minima with providing a virtual target point. The resultant force exerted on the mobile robot by obstacles and target points on the driving path and Euclidean distance between the two-dimensional coordinates of the mobile robot and the two-dimensional coordinates of the end point are used as inputs to the fuzzy logic system. The relative Angle of the virtual target point coordinates to the robot coordinates and the gain coefficient of the gravitation function generated by the virtual target point is the output of the fuzzy logic system.

The universe of discourse defined after normalizing the resultant force F is [0,1], and the corresponding fuzzy subset is {f_s, f_m, f_l}. The universe of discourse defined after normalizing distance is [0,1], and the corresponding fuzzy subset is {distance_s, distance_m, distance_l}. The universe of the output angle angel is [0,1], angel is $[0, \frac{\pi}{3}]$ after clarity, and the corresponding fuzzy subsets are {angel_s, angel_m, angel_l}. The universe of the gain coefficient k of the gravitation function generated by the virtual target point is [0,1], and the corresponding fuzzy subset is {k_s, k_m, k_l}, and the range of k is [0,5] after clarity. The input and output variables are selected as triangular membership functions. Figure 4 illustrates the membership functions of the above parameters

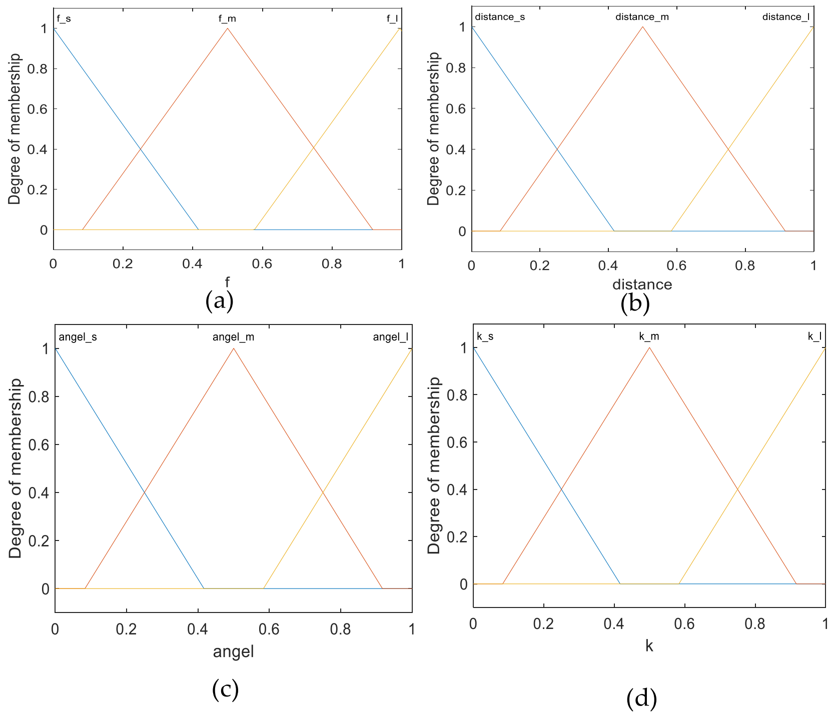


Figure 4. (a) The membership function of F; (b) The membership function of distance; (c) The membership function of angel; (d) The membership function of k.

Table 1 is the fuzzy rule table set in this article.

Table 1. Fuzzy rule table

	input		output	
	F	distance	angel	k
1	F_L	distance_s	angel_s	k_m
2	F_L	distance_m	angele_m	k_m
3	F_L	distance_l	angele_m	k_l
4	F_M	distance_l	angel_l	k_l
5	F_M	distance_m	angele_m	k_m
6	F_M	distance_s	angel_s	k_s
7	F_S	distance_s	angel_s	k_s
8	F_S	distance_m	angel_s	k_s
9	F_S	distance_l	angel_s	k_s

The coordinates of the virtual target point with respect to the mobile robot are derived by the relative Angle between the coordinates of the virtual target point and the coordinates of the mobile robot, and the mathematical formula used in the derivation is Equation 10.

$$\begin{cases} x_{virtual} = x + \rho\cos(angel) \\ y_{virtual} = y + \rho\sin(angel) \end{cases} \quad (10)$$

The virtual target point will generate a gravitational potential field with a gain coefficient k, and the gravitational force exerted by this virtual gravitational potential field on the mobile robot can be passed through Equation 11.

$$F_{virtual} = k\rho(q_{rob}, q_{virtual}) \tag{11}$$

The resultant force exerted by the mobile robot after adding the virtual target point can be calculated by Equation 12.

$$F` = F + F_{virtual} \tag{12}$$

Figure 4 illustrates the force analysis of the robot after adding the virtual target point.

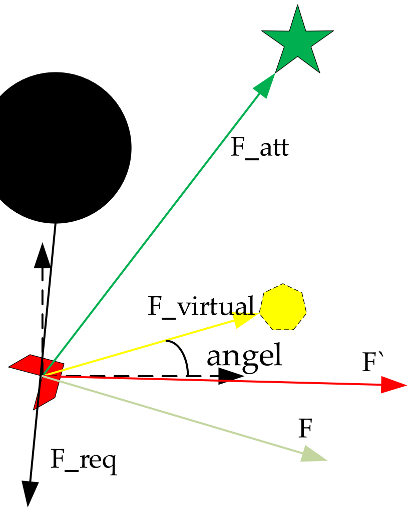


Figure 5. Force analysis of mobile robot under potential field and virtual potential field composite field.

4. Analysis of Experiment and Simulation Results

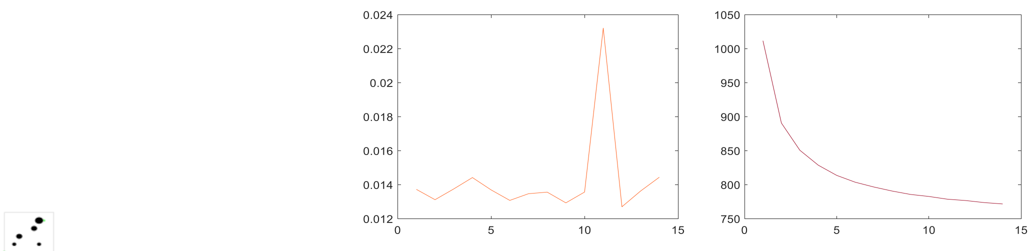
The simulation parameters adopted by the APF are obtained from Table 2.

Table 2. simulation parameter Settings

Gravitational gain coefficient	Repulsion gain coefficient	The obstacle affects the maximum radius	The robot moves in step	Maximum number of iterations	Start point	End point
2	20	5	0.01	3000	[0,0]	[8,8]

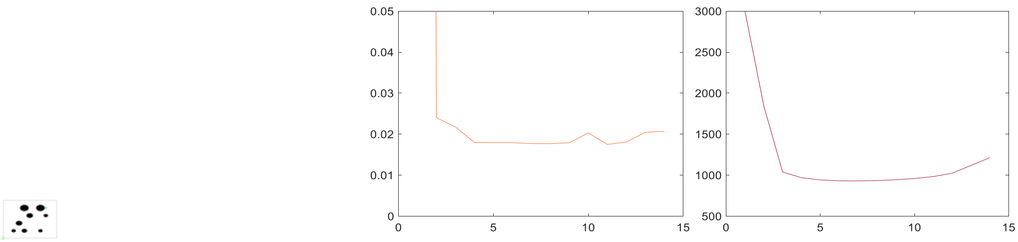
4.1 Exponential Parameter Selection for Distance Regulation Factor

The value of the distance factor index parameter in Section 3.1 needs to be tested repeatedly to select the better value. This is shown in Figures 6 and 7 and Tables 3 and 4.



(a) (b) (c)

Figure 6. (a) Test Environment 1; (b) Relation between exponential parameter and running time of algorithm; (c) Relation between exponential parameter and the number of iterations.



(a) (b) (c)

Figure 7. (a) Test Environment 2; (b) Relation between exponential parameter and running time of algorithm; (c) Relation between exponential parameter and iterations.

Table 3. Operation effect of under different exponential parameter in environment 1.

Testing environment	Exponential parameter	Iterations	Time/s
1	1	1012	0.013597
	2	891	0.0130416
	3	851	0.013433
	4	829	0.013341
	5	814	0.014008
	6	804	0.015409
	7	797	0.012591
	8	791	0.012743
	9	786	0.013052
	10	783	0.015824
	11	779	0.012262
	12	777	0.012372
	13	774	0.013064
	14	772	0.013893

Table 4. Operation effect of under different exponential parameter in environment 2.

Testing environment	Exponential parameter	Iterations	Time/s
2	1	2489	2.896920
	2	1676	1.58279
	3	1584	1.125955
	4	1783	0.711311
	5	2115	0.603508
	6	1313	0.26592
	7	1119	0.023883
	8	1050	0.022856
	9	1019	0.021648
	10	1010	0.022836
	11	1017	0.022301
	12	1045	0.022350
	13	1125	0.023694
	14	1411	0.027736

The results obtained from the analysis of Tables 3,4 and Figures 6,7 are that the iterations and the path planning time will change with the change of the value of the distance factor exponent parameters n. By testing, 10 is chosen as the exponent parameter.

4.2 Simulation Result Analysis of Solving Unreachable Target

The Figure 8 show the simulation results of the robot applying APF when the target is not reachable in a complex environment.

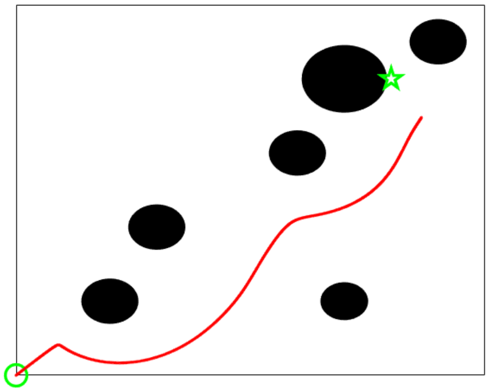


Figure 8. Simulation diagram of unreachable targets.

After the repulsion field function is optimized by adjusting the gain coefficient, the target unreachable problem is solved, Figure 9 shows the simulation results.

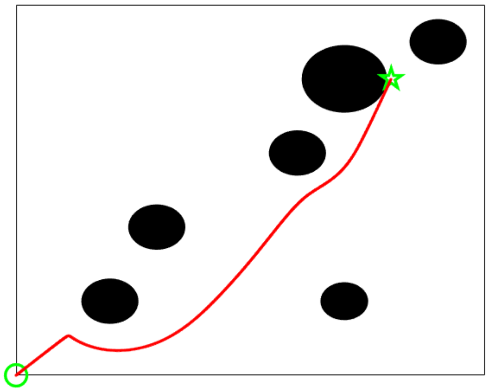


Figure 9. Simulation diagram where the target inaccessibility is solved.

4.3 Simulation Test of FUZZT_APF

Although the phenomenon of unreachable goals can be addressed by optimizing the coefficient of the repulsive potential function, it does not mean that the mobile robot will not encounter local minimum in complex environments. Figure 10 point out that the improvement of repulsive potential field function alone is not enough to make APF suitable for more complex environments.

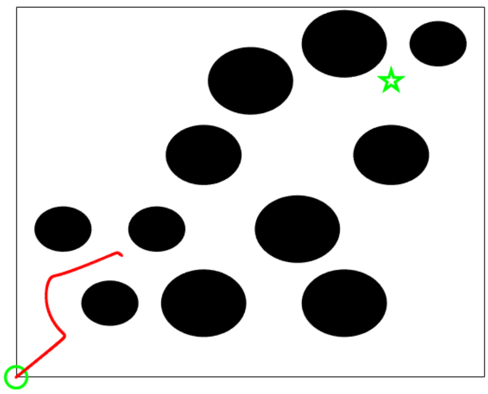


Figure 10. The modified repulsion function suffers from local minima in complex environments.

The scheme of generating virtual target points by coupling fuzzy logic algorithm can apply escape force to a robot trapped in a local minimum to help it continue to operate, Figure 11 shows the operation effect of this algorithm.

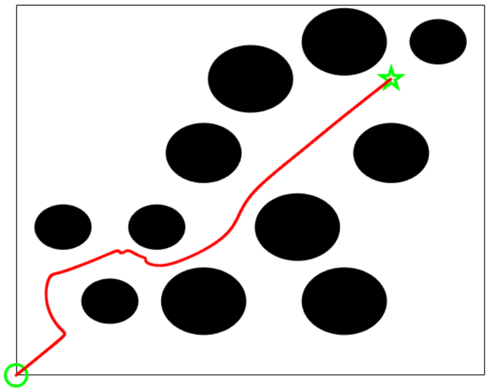


Figure 11. The FUZZY_APF helps the robot get rid of the local minimum.

It was also tested in different complex environments, as shown in Figures 12,13.

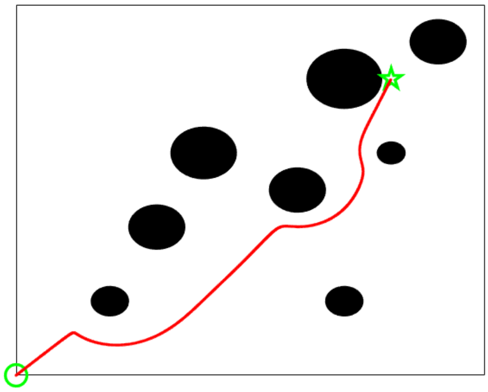


Figure 12. Result of the operation of the FUZZY_APF in Environment 2.

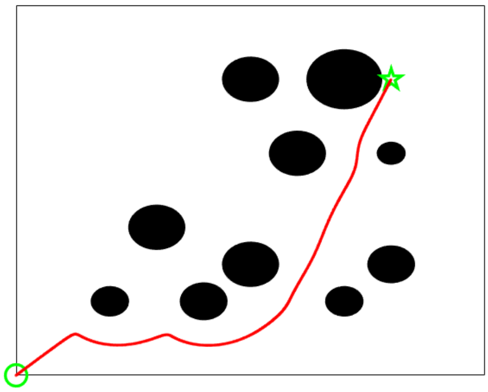


Figure 13. Result of the operation of the FUZZY_APF in Environment 3.

4.4 Performance between FUZZY APF and APF

formance of the APF and the FUZZY_APF will be compared by two parameters: iterations and the path planning time.

Figures 14,15,16,17,18,19 show the simulation run result graphs of APF and FUZZY_APF in three different environments.

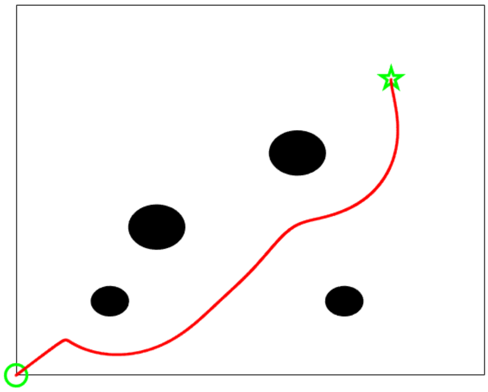


Figure 14. The route planned by the APF in environment 1

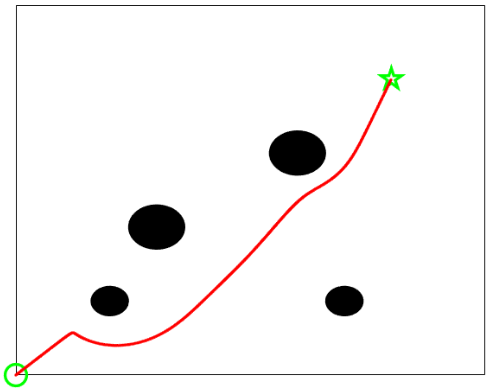


Figure 15. The route planned by the FUZZY_APF in environment 1.

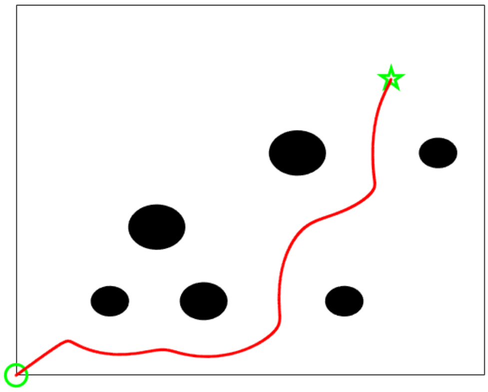


Figure 16. The route planned by the APF in environment 2

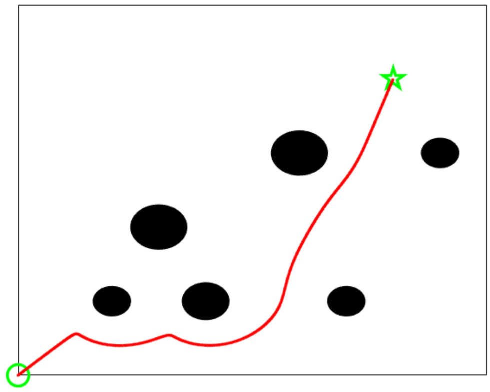


Figure 17. The route planned by the FUZZY_APF in environment 2

Table 5 records the performance comparison of the APF and the FUZZY_APF in two different environments including the iterations and the algorithm running time.

Table 5. Performance comparison of the APF and the FUZZY_APF

Testing environment	Algorithm	Run time/s	Iterations
testing environment1	APF	0.010420	918
	FUZZY_APF	0.006595	782
testing environment2	APF	0.016177	1147
	FUZZY_APF	0.015386	947

It can be seen from Table 4 that the FUZZY_APF retains the advantages of the short running time of the APF, and the planned route is smoother.

5. Discussion

Due to the good obstacle avoidance effect, small amount of calculation, and easy implementation, many engineers and scholars have used the APF in mobile robot path planning since it was proposed. But in a complex environment, the mobile robot using this algorithm is easy to occur local minimum and the target is unreachable. To enable the APF to adapt to more scenarios, it still maintains superior performance in complex environments, many scholars have proposed different optimization schemes. Most of the directions are to optimize the potential field function model or set up virtual obstacles and virtual target points to provide an escape force, but these schemes still cannot work in complex environments, and the calculation amount increases and the real-time obstacle avoidance effect decreases.

Euclidean distance between two coordinates of the robot and the destination is used as an adjustment factor to multiply with the repulsive force gain coefficient so that the originally fixed repulsive potential field function gain coefficient becomes adjustable. The exponential parameter of the adjustment factor is also obtained by several simulations. This scheme can address the target unreachable problem of the APF when the repulsive force is greater than or equal to the attractive force. Figures 8 and 9 validate the proposed scheme. However, the optimization of the repulsive potential field function is not sufficient to make the mobile robot not encounter the local minimum problem in a complex environment that is too far from the goal point, as shown in Figure 10. Therefore, this paper further proposes a scheme coupled with the fuzzy logic algorithm, which uses the fuzzy logic algorithm to generate a virtual target point in a range of 0 to 30 degrees relative to the mobile robot. The virtual target point will generate a virtual gravity field to provide gravity for the robot trapped in a local minimum so that it can deal with the local minimum problem in a complex environment, as shown in Figure 11. The simulation results in Figures 14-17 and Table 5 shows that compared with the APF, FUZZY_APF plans smoother routes with shorter route lengths and less planning time. In future work, it is necessary to further optimize the fuzzy logic system and further determine the exponent value of the optimization coefficient of the repulsion function. At the same time, FUZZY_APF is deployed in a more complex environment for performance verification.

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