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Improved artificial potential field to solve the problem of local minimum

Hao Jiang

Nanjing Agricultural University, Nanjing, Jiangsu, China

9203011213@stu.njau.edu.cn

Abstract. The artificial potential field approach is a traditional method that is frequently used for local path planning, but in order for it to be successful, it requires more than unreachable target sites, local minimums, and oscillation difficulties. An enhanced method that is based on discretized sampling was presented as a potential solution to these issues as a result of this information. In the first place, a decision must be made regarding whether or not to enter the local minimum mark. In order to free ourselves from the confines of the local minimum, we subsequently devised a motion that was perpendicular to the direction in which the object was being moved. In the end, a regression search is carried out in order to further hone in on the correct path. The results of the simulation show that this method is capable of efficiently handling the local minimum problem and providing appropriate paths, as demonstrated by a comparison between the conventional method and the enhanced method.

Keywords: local minimum, artificial potential field, path optimization.

1. Introduction

Route planning is a crucial area of study for mobile robots. Robots frequently use the artificial potential field approach, genetic algorithms, and PRT algorithms to implement self-sufficient obstacle avoidance and local path planning.

Khatib first proposed the artificial potential field method, a virtual force method [1]. The fundamental concept is to create a potential virtual field in which a robot is subject to the goal's gravitational pull and the obstacles' repulsion force. Under the influence of combined energies, the robot eventually reaches its destination. Due to its low computational effort, simplicity of principle, and low hardware requirements, the artificial potential field approach is extensively used and has spawned numerous variants. Several issues exist with the conventional artificial potential field approach:

- The objective close to the obstruction is inaccessible.
- The robot rapidly reaches local minimum points.
- It is simple to generate oscillations close to the obstacle.

In response to these problems, many scholars have put forward a lot of improved methods. Chen et al. proposed an approach combining local minimum judgment with escape and path optimization [2], and Rostami et al. proposed a method to enhance the artificial potential field method [3]. Gao et al. used the target point search algorithm to determine the best target point for each robot. Then they improved the potential field function to achieve multi-robot uniform formation [4]. Aiming at the path planning problem in an uncharted environment, Zhu et al. put forward "running to the target behavior" and "walking along the wall" to leap away from a local minimum point [5]. After a mobile robot fell into a local minimum, Luo et al. proposed a method to set the intermediate goal to make the robot leap away from the local minimum point [6]. Xing et al. has optimized the potential field function, solved the problem of local minimum and the problem of unreachable targets near obstacles, and put forward a regression search approach to optimize the path further globally [7].

In this paper, in order to resolve the problem that the robot is easy to enter local minima in traditional sampling approach, a detailed strategy of discretized sampling is put forward to resolve the path.

2. Traditional artificial potential field model

Khatib came up with the artificial potential field approach, which is a virtual force method. The goal has an attraction force on the mobile robot, and the obstacle has a repelling force on the mobile robot. Figure 1 shows how the robot moves because of these two forces.

The total potential field function is

$$U(q) = U_{att}(q) + U_{rep}(q) \tag{1}$$

The gravitational field function is

$$U_{att}(q) = \frac{1}{2} K_a \rho^2 (q, q_{goal}) \tag{2}$$

Where K_a is the gravitational gain coefficient; $q_{goal}$is the coordinates of the goal; $(q, q_{goal})$is the distance of the robot from the goal. The repulsive field function is

$$U_{rep}(q) = \begin{cases} \frac{1}{2} K_r \left(\frac{1}{\rho(q, q_{obs})} - \frac{1}{\rho_d} \right)^2 & \rho(q, q_{obs}) < \rho_d \\ 0 & \rho(q, q_{obs}) \geq \rho_d \end{cases} \tag{3}$$

Where K_r is the repulsive gain coefficient; $\rho(q, q_{obs})$is the interval from the mobile robot to the closest obstacle; ρ_d is the distance threshold. When the interval between the present location and the obstacle is less than ρ_d, the mobile robot will be repulsed. The robot will move in the direction where the total potential field is falling fastest, so the resultant force is

$$F(q) = -\nabla U(q) = -\nabla U_{att}(q) - \nabla U_{rep}(q) \tag{4}$$

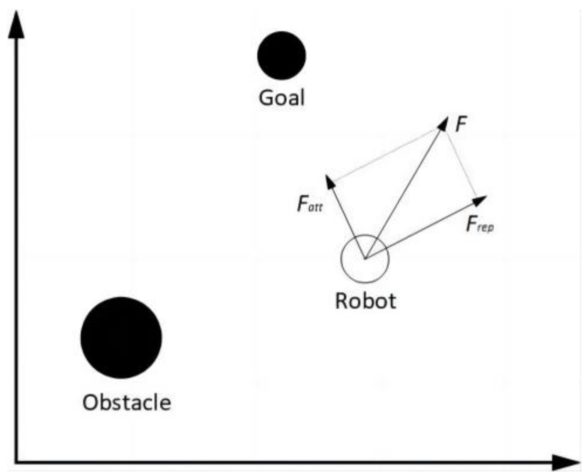

Figure 1. Force analysis of traditional artificial potential field.

The local minimum problem occurs in the conventional artificial potential field approach. No robot is unable to reach the destination when there are impediments in its path because the attraction of the robot is constantly diminished and the repelling force is increased. The robot enters the local minimum if it reaches a point during its motion where the forces of gravity and repulsion are equal in strength but in the opposing directions. Robot movement is particularly prone to oscillation, therefore the robot cannot continue moving in the direction of the destination if the path is limited and has barriers on all sides.

3. Improved method

Figure 2 depicts the flowchart of the robot's main programme based on the enhanced discretized artificial potential field method.

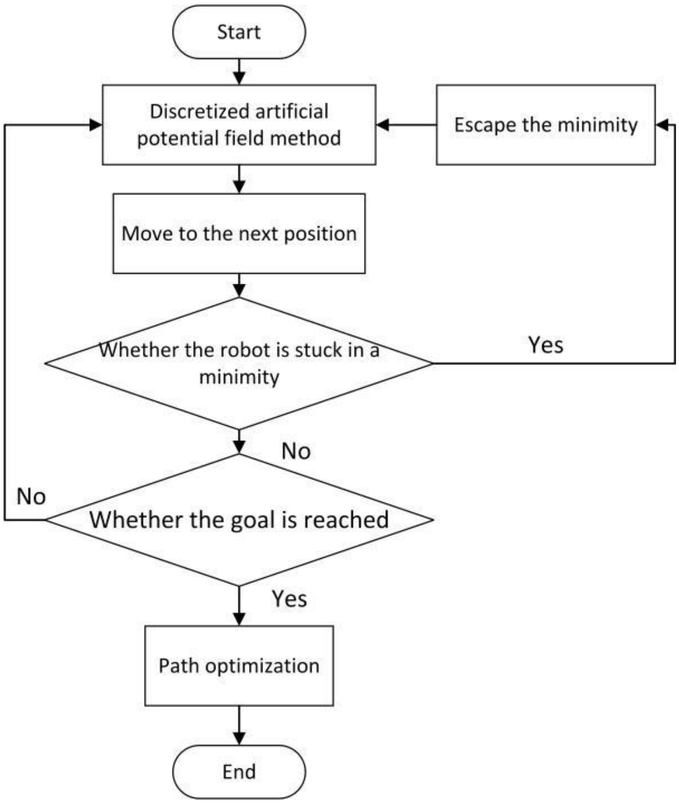

Figure 2. Algorithm workflow.

3.1. Exploration of fixed directions

3.1.1. Sampling-based analysis. Discretized artificial potential field approach is a kind of artificial potential field approach based on discretized sampling. A robot is typically viewed as a particle in the standard artificial potential field approach, just sampling and measuring the particle's force in the field and planning the next movement using the force, allowing the robot to travel in any direction. The points surrounding the robot serve as the sampling object in the discretized artificial potential field method. The force of these points is measured, and the sampling point is chosen as the path point using a predetermined strategy. The robot is only able to move in one direction and with a certain step size while in motion. The discretized artificial potential field method requires less computing power and has a much lower chance of hitting the local minimum. The path is not sufficiently smooth, which is a drawback, and the path optimisation algorithm repair will be introduced later.

3.1.2. Detailed principle. When discretizing the robot, first treat it as a particle, then use this particle as the center of the circle, move the step as the radius to draw the circumference, evenly divide and number eight sampling points on the circumference, calculate the force of these eight sampling points in the potential field, and choose the point where the force is the strongest as the path point, as shown in Figure 3. (if the two points are the same force, the significant numbered point is preferred). And so on till the robot reaches its destination.

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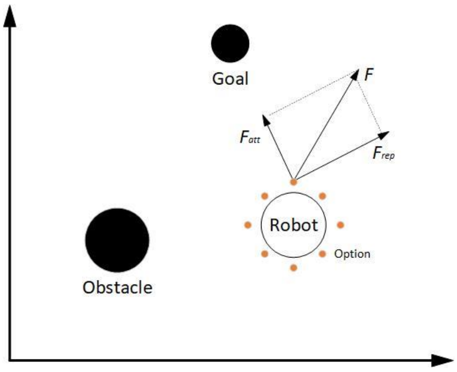

Figure 3. Force analysis of discretized artificial potential field.

3.2. Judgment and escape from local minimum

As is shown in Figures 4-6, local minima in the potential field can occur for a bunch of reasons, and the main ones are:

(1) The repulsive force is just equal to the attraction;

(2) The drone is trapped in a small space surrounded by multiple obstacles, and the attraction and the repulsion force are equal in magnitude and opposite direction;

(3) There are obstacles close to the goal [8].

In the process of movement, the robot constantly records its position and direction, assuming that the current position of the mobile robot is Pk(xk, yk, zk). The position of the previous moment is Pk–1(xk–1, yk–1, zk–1), if ||Pk–Pk–1||<ε and||Pk–Pg||<ξ, it is judged that the mobile robot has entered the local minimum point, and the position of the local minimum is Pk–1 if ||Pk–Pg||<ξ, it is judged that The robot has met its goal. ε,ξ is a constant greater than 0.

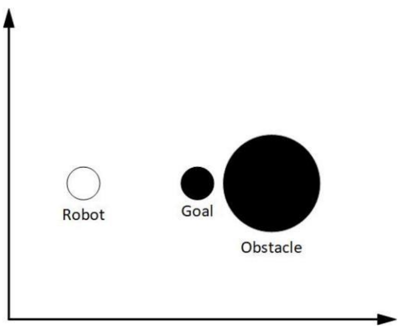

Figure 4. Typical local minimum-a obstacle is close to the goal.

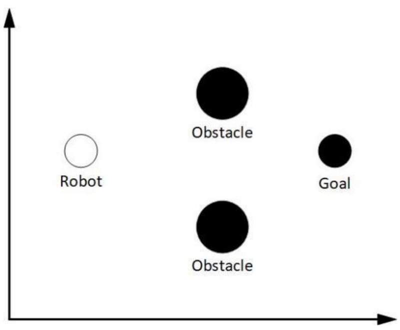

Figure 5. Typical local minimum-attraction equals repulsion.

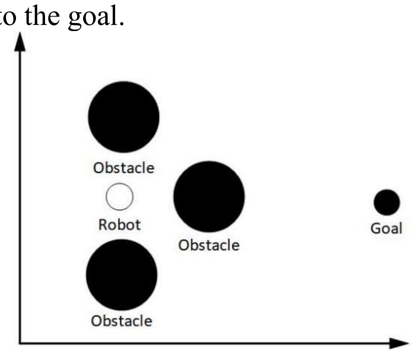

Figure 6. Typical local minimum-obstacles create tight space.

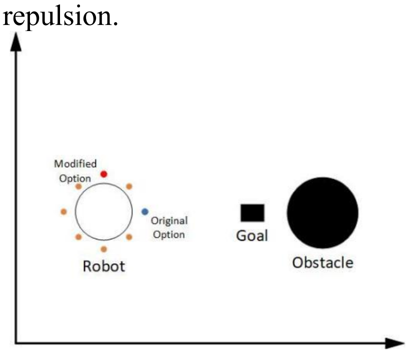

Figure 7. Escaping from a local minimum.

As seen in Figure 6, if a robot is found to have entered a local minimum point, it will move 90 degrees away from the intended path. It is necessary to add the number of movements based on the original movement three times if the judgement is still within the local minimum. To do this, multiply the number of its original option point by two or two less (typically add two), choose this option point three times in a row as the moving option point of its movement, and then make a judgement of the local minimum. If it has been determined that it is not in the local minimum, you can continue to move. Decide on the local minimum, then add up all the moves up till the mobile robot gets away from the local minimum. Figure 7 demonstrates how a robot escapes from a local minimum.

Allowing the mobile robot to travel in any direction after it enters a local minimum point can cause the mobile robot to momentarily move from the local minimum point. Because it is simpler to escape from the local minimum if the angle between the direction of escape and the initial direction of travel is too small, it is decided to proceed in a direction that is 90 degrees from the original path of movement. The likelihood of the robot swaying back and forth close to the local minimum rises as a result.

3.3. Path optimization

The straight line segment between two points is the shortest, and the robot need to have the shortest path and the least time to reach the target from the starting point. Although the discretized artificial potential field approach solves the problem of elusive targets and local minimum points near obstacles, the planned path could be more optimal. The path optimization method based on the regression search method is described below.

As seen in Figure 8, the discrete artificial potential field approach's path for the point set is depicted by {P1,P2,⋯, Pn}n points, connecting P1 and P2, and if the line segment P1 P2 has no intersection with the range of the obstacle safety distance l0, connect P1, P3, and go in turn. Suppose there is no intersection between P1Pi and the range of the safety distance of the obstacle, and there is an intersection point between P1Pi+1 and the range of the safe distance of the obstacle. In that case, P1Pi is selected as the optimized path segment. Starting from Pi, repeat the process until it reaches the target point. The optimized barrier-free path using this algorithm is globally optimal [9].

This article studies the discretized artificial potential field method, so the distance is constant for each movement, and the selection of {P1,P2,··,Pi,·,Pn} is determined according to the set of points planned by the discretized artificial potential field method.

In fact, {P1,P2,··,Pi,⋯,Pn} can select all points in the planned point set, or random points within a suitable distance, that is, PiPi+1<D, the smaller the value of D, the denser the selected points, the more accurate the path optimization, but the more iterations, the longer the calculation time. In theory, the most intensive case of points is to select all points in the planned point set, but in practical applications, the value of D can also be increased to reduce the calculation time [10].

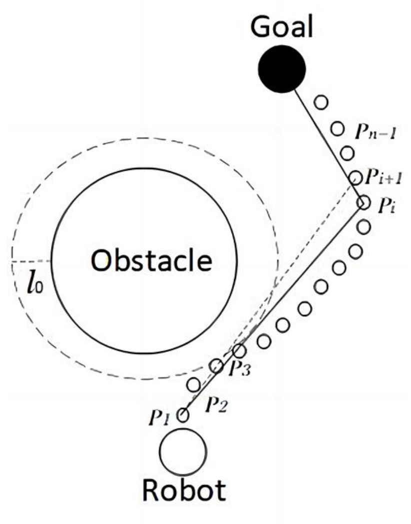

Figure 8. The detailed process of path optimization.

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4. Simulation verification

This essay uses MATLAB as its experimental platform. The robot is viewed as a particle in the 2D plane in this simulation. The path planning chooses the case of a single robot, the attractional field gain coefficient Ka is 5, the repulsive gain coefficient of the obstacle and the robot is Kr=100, the influence distance of the obstacle is 10, the circumferential radius of the alternative point is 0.8, and the size of each obstacle is consistent. The destination coordinates and the robot's initial coordinates are predetermined. The onboard sensor typically gathers the robot's coordinate information during the actual application procedure, which is contradictory with the paper's study focus and won't be covered in this section.

4.1. Feasibility testing

First, the feasibility of the discretized artificial potential field approach is evaluated, and then a map is generated at random to determine if the mobile robot can complete the path planning from the starting point to the destination.

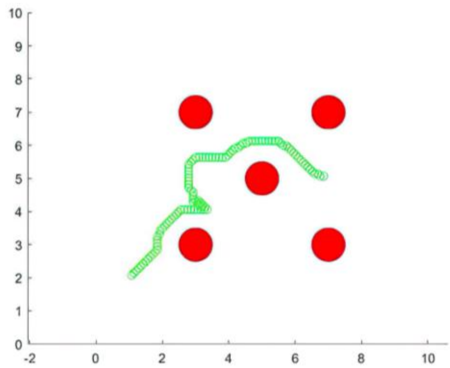

Figure 9. Feasibility testing of discretized artificial potential field approach.

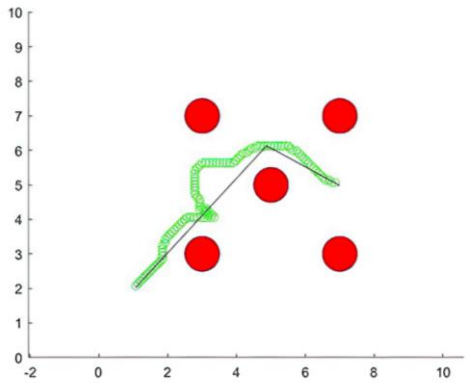

Figure 10. Path optimization testing of discretized artificial potential field approach.

The outcomes are displayed in Figure 9. from which it can be obtained that in the case of a random map, the discrete artificial potential field approach can avoid barriers and complete path planning. Regression search is used to optimize the robot's path, which is represented by the black line segment in Figure 10.

4.2. Traditional artificial potential field testing

In the following simulations, the feasibility of the traditional artificial potential field approach is tested when encountering three typical local minimums, as shown in Figures 11-13. The conventional artificial potential field approach is incapable of addressing the local minimum problem, and all the robots are stuck in the local minimum.

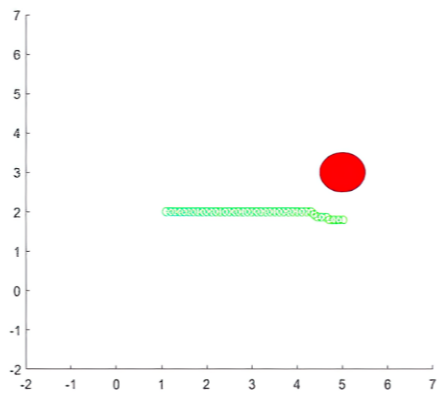

Figure 11. Traditional artificial potential field testing-a obstacle is close to the goal.

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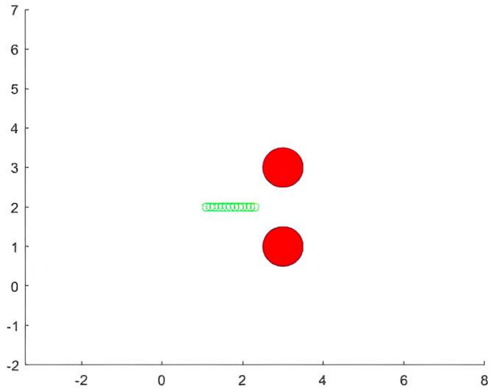

Figure 12. Traditional artificial potential field testing-attraction equals repulsion.

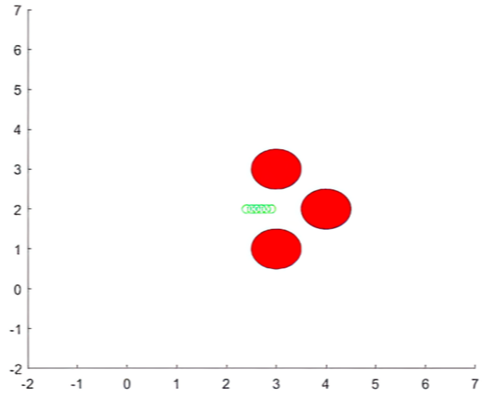

Figure 13. Traditional artificial potential field testing-obstacles create tight space.

4.3. *Improved artificial potential field testing*

The discretized artificial potential field approach's efficacy is then evaluated by using three common local minimums, as shown in Figures 14-16; the mobile robot moves from the local minimum point and achieves the goal after the problem of robots entering a local minimum point is successfully resolved by the discretized artificial potential field approach.

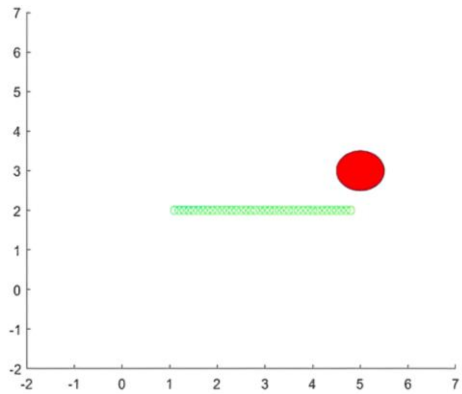

Figure 14. Discretized artificial potential field testing -a obstacle is close to the goal.

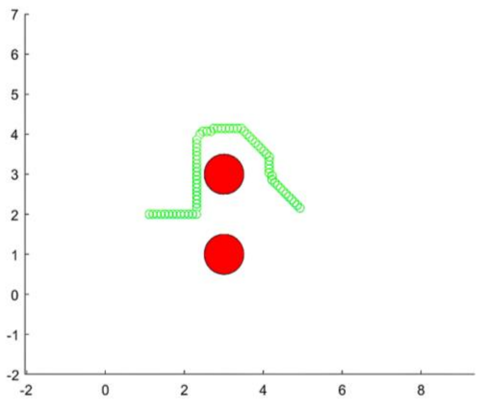

Figure 15. Discretized artificial potential field testing -attraction equals repulsion.

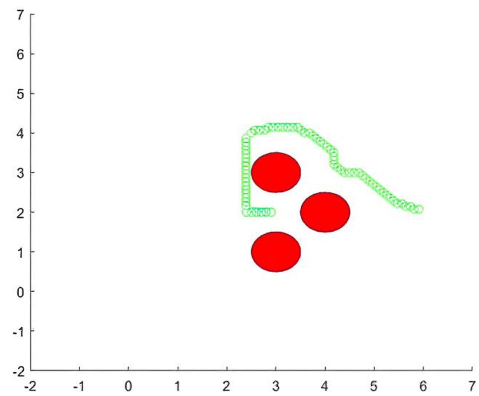

Figure 16. Discretized Improved artificial potential field testing-obstacles create tight space.

5. Conclusion

This paper proposed a discretized artificial potential field method that could judge and escape from a local minimum, solving the issue of robots entering a local minimum point and elusive targets. The

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discrete path planned by the discretized artificial potential field approach is then optimized by regression search. The simulation findings demonstrate that three typical local minimum problems can be handled using the discretized artificial potential field approach for path planning.

In this essay, the primary research is the effectiveness of the discretized artificial potential field approach in a two-dimensional plane, potential static field, and path planning of a single robot, and future research will focus on the discretized artificial potential field approach in three-dimensional space, dynamic potential field, and multi-robot path planning. Of the three typical local minima points in this study, they all belong to simple map cases. In the future, research will be carried out on applying artificial potential field methods for discretization in complex map situations.

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