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Improved artificial potential field route planning method based on stochastic perturbation

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Abstract. As a typical route planning algorithm, the APF method has been widely used in robotics, autopilot and other fields. However, it also has weakness in local optimal point. In computer science and mathematics, stochastic perturbation is an accepted approach that can assist optimization algorithms leave the local optimal solution and achieve the global optimal solution as well as improve robustness and adaptability in specific application situations. therefore, the problem can be successfully solved by using stochastic perturbation. In this article, the traditional APF improved through stochastic perturbation. When the robot is running in an APF, the distance between the robot and the target point is calculated at all times. If the distance between the robot and the target point remains unchanged for a period of time or if the stop point oscillates, it is determined whether the robot has reached the target point at this time. If not, it is determined that the robot has fallen into a local optimal point at this time. After completing the judgment, stochastic perturbation is applied to the robot, causing it to jump out of the local optimal point and continue to navigate to the target point. The results of the comparison between the paths generated by the traditional method and the improved method validate the effectiveness of this method.

Keywords: path planning, artificial potential field, local optimal point, stochastic perturbation.

1. Introduction

Path planning refers to finding a collision-free path from a starting state to a target state in an environment with obstacles based on certain evaluation criteria. The related methods are of great significance in the automation of robot and unmanned aerial vehicle tasks. After years of development, many path planning methods based on different principles have emerged. The ant colony algorithm, that simulates the behaviour of ants in finding paths and has the ability of global optimization, proposed by Dorigo et al. is a metaheuristic algorithm widely used in path planning and optimization problems. In addition, simulated annealing algorithm, genetic algorithm and other algorithms are also widely used in path planning and optimization problems [1].

First proposed by Khatib et al., the artificial potential field method has been widely used in robot path planning [2]. However, it also has weakness in local optimal point. Therefore, some researchers have proposed improvement and optimization methods for the problems of the APF. For example, Kucner et al. proposed an artificial potential field method based on domain segmentation, which divides the search space into multiple subspaces and adopting different potential field functions in searching

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process, thus increasing the ability of local search and global search in the algorithm[3]. An artificial potential field method based on gradient descent was suggested by Jung et al.[4], which avoids local optimal solutions by introducing gradient descent method and achieves good optimization results.

Although these optimization methods can effectively increase the search ability of the artificial potential field method, complex calculation and optimization strategies still required. As a simple and effective technique, random perturbation enables the artificial potential field method better escape from local optimal solutions, improving the global search ability of the algorithm. Based on this, this paper purposes an improved method. When the robot stops moving in the end, it is judged whether it has reached the target point. If it does not, and oscillates around the point, it is considered to have fallen into a local optimal point. At this point, stochastic perturbation is added to the robot to help it jump out of the local optimum. When the robot leaves the point, the stochastic perturbation stops. If it falls into a local optimum again, the above steps are repeated until the robot reaches the target point.

2. Traditional artificial potential field method

The potential field model serves as the foundation for the and approach, an optimization technique whose target function is imagined as the movement of a robot in a potential field. Besides, the lowest potential energy point is discovered by simulating the robot's movement process to achieve the best result[5]. The major stages are as follows:

2.1. Potential field model definition

Graviton and repulsion usually constitute up the two components of the potential field model. While the repulsion drives robots away from the local optimal point, the graviton pulls robots toward the goal location. The both components' weights can be modified to show an impact on the outcomes[6].

$$U(q) = Uattractive(q) + Urepulsive(q) \tag{1}$$

In this formula, $U(q)$represents the relationship between the resultant force field and the variable q, $Uattractive(q)$ represents the relationship between the attractive field, $Urepulsive(q)$represents the relationship between the repulsive field

The controlled object is exposed to both repulsion and gravity in the composite field formed by these two potential fields. The combination of repulsion and gravity force directs the motion of the controlled object to search for a collision-free obstacle avoidance path.

And function should be characterized as follows: 1. non-negative and continuously differentiable; 2. the repulsion field's force increases with proximity to the obstruction; 3. the gravitational field's intensity lowers with distance from the target area.

The following parameters of the gravity and repulsion potentials are established here;

Graviton field

$$U_{att} = \frac{1}{2} K_{att} P_0^m \tag{2}$$

In this formula, K_{att} is the positive coefficient of the gravity potential field, P_0 is the linear distance between the robot and the target point; M is gravity potential field factor.

$$F_{att}(P_0) = -\nabla U_{att}(P_0) = -K_{att} P_0 \tag{3}$$

F_{att} means the negative derivative of the gravity potential field function, presenting the fastest directional changes in the gravity potential field and the degree of gravitational force is declared by the gravity potential field function on the unmanned vehicle and the target function

Repulsion field:

$$U(P_g) = \begin{cases} \frac{1}{2} K_{rep} \left(\frac{1}{P_g} - \frac{1}{\rho} \right)^2, & P_g < \rho \\ 0, & P_g \geq \rho \end{cases} \tag{4}$$

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Where ρ is the maximum function range of the obstacle that generates a repulsive force on the unmanned vehicle, P_g is the distance between the obstacle and the unmanned vehicle, K_{rep} is the positive proportion coefficient in the repulsion potential field.

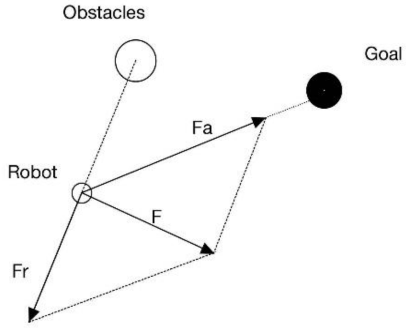
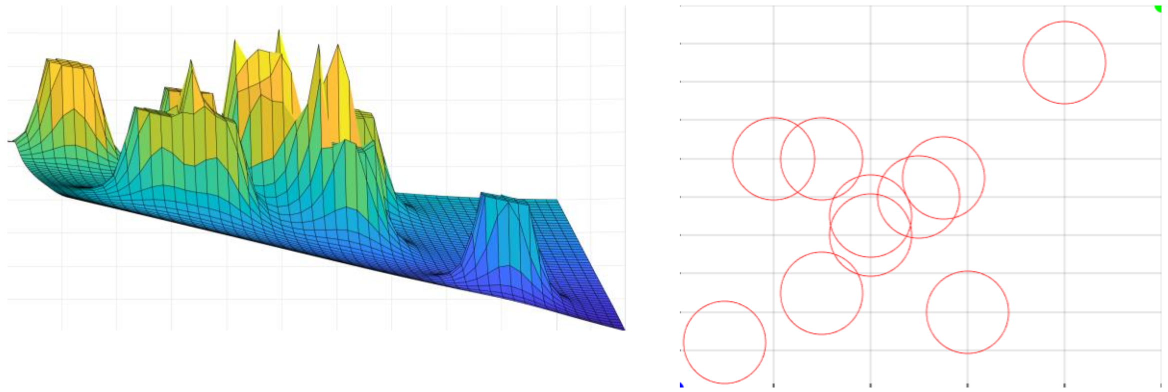


Figure 1. Resultant Angle direction in APF.

The Figure 1 indicates the relationship between the repulsive force of obstacles and the attractive force of the target point.

2.2. Obstacle creation in the map

The distribution of obstacles in the market is displayed in Figure 2.



(a) (b)

Figure 2. Force value of APF method. (a) join forces of repulsion and attraction;(b) The coordinates of obstacles in 2d map.

In Figure 2, the gravity and repulsion arising from each obstacle under the defined and are illustrated, with the bumps indicating the magnitude of the repulsion field and the height of the longitudinal coordinate of the ramp showing the magnitude of the gravity field.

2.3. Calculation of potential energy values

The current potential energy value can be derived by calculating the position and velocity of each robot, as well as the objective function value.

2.4. Robot position and velocity updates

The inertial weights, acceleration and historical information of robot position and velocity will support the update of robot position and velocity. Simultaneously, the velocity magnitude and position range are supposed to be limited to prevent overrunning the search space.

$$q = q + stepsize \times compositeForce \tag{5}$$

In this formula, q stands for the real time position of the example, $stepsize$ indicates the distance of the step, $compositeForce$ refers to the combined force of the gravity and repulsion fields.

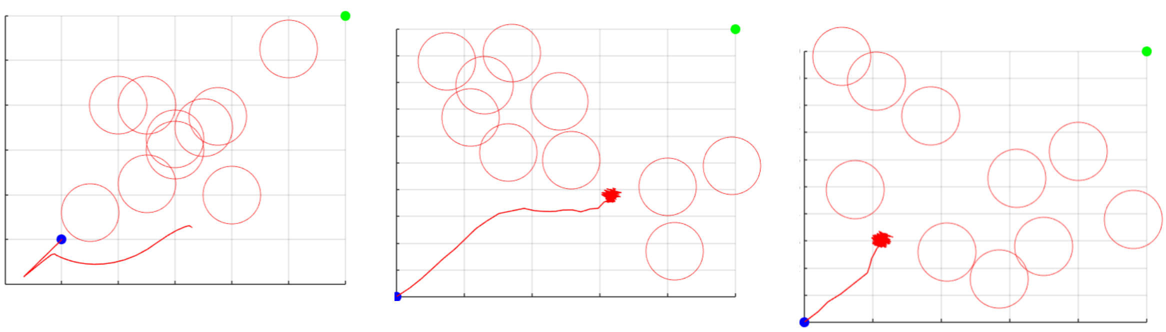
2.5. Termination condition judgement
The iteration will be terminated when the distance between the robot and the target point becomes a constant value or has a small range of variation.

$$X = \sqrt{q^2 + q_{goal}^2} \tag{6}$$

Where X is the distance between the robot and the target point, $q$is the location of robot, q_{goal} is the target point position.

2.6. Limitations in APF algorithm
Served by path planning algorithm, the APF algorithm works as a potential energy field bases algorithm. In its basic principle, the robot and its surroundings are considered as charged robots, while the potential energy of the robot's location becomes zero and the potential energy of obstacles and target points influenced by the distance, forming a potential energy field. Then the robot designs its path through minimum total potential energy. However, there are limitations in the APF algorithm.

It is easy for the APF algorithm to be trapped in local minima, resulting in a failure to reach the optimal solution[7]. In practice, the artificial potential field method frequently fails to work well because of the existing local optimal point. The presence of multiple local optimal point in the objective function makes it difficult for the algorithm to escape from the trap and continue the search for a more optimal solution. When the distance between the robot and the obstacle surpasses the influence range of the obstacle, the repulsive potential field shows no impact on the robot. Therefore, the potential field method can only address the obstacle avoidance problem in the local space and faces blind spot in global information, which also causes it easy to fall into local optimal point in the process of usage. The term "local optimal point" refers to the influence of multiple functions in some regions of the joint distribution space of the gravity potential field function and the repulsion potential field function, whose combined forces are minimal and cannot escape from the point. Moreover, the more obstacles there are, the greater the possibility of creating a local optimal point.



(a) (b) (c)

Figure 3. Different situations of local optimal point. (a)-(c) are different conditions.

As shown in Figure 3, the robot has no access the target point and oscillates at the local optimal point. The red circle represents the function range of the obstacle in repulsion field.

3. Improved method
On the basis of the traditional artificial potential field method, the stochastic perturbation artificial potential field method adds some random terms for the total potential field to make it more possible for the algorithm to leave the local optimal point. In particular, it can express the total potential field as the following form:

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$$F_{total} = F_{att} + F_{rep} + F_{random} \quad (7)$$

F_{att} and F_{rep} are the attraction and repulsion fields, respectively, while F_{random} serves as a random term. F_{random} can be regarded as a random vector, a random number, or some other random term which aims to move the robot in a different direction in each time step, thus out of the local optimal point.

Adding a random vector to the total potential field gives the simplest method of stochastic perturbation [8], which is

$$F_{total} = F_{attract} + F_{repulse} + k \times randn(1,2) \quad (8)$$

In which, k refers to the weight of the random term, $randn(1,2)$ indicates the function generated by the random number in line with the normal distribution. 1 and 2 represents the number of rows and columns of the random term, respectively. In actual application, the value of k can be modified depending on the specific problem to achieve the best optimization effect [9].

In addition, the stochastic perturbation can also be carried out in the attraction and repulsion fields, which is

$$F_{attract} = F_{goal} \times k_1 + F_{goal\,random} \quad (9)$$

$$F_{repulse} = \sum F_i \times k2 + F_{i\,random} \quad (10)$$

Where F_{goal} serves as the attraction field potential function and $F_{goal\,random}$stands for the random term of the attraction field. F_i refers to the obstacle repulsion potential function and $F_{i\,random}$ Figures for the repulsion field. k_1 and $k2$ refer to the weights of the attraction and repulsion fields, respectively.

By introducing stochastic perturbation, the robot can be allowed to move in different directions while encountering the same environment, thus more possibilities come out to make it easier to escape from the local optimal point and acquire a better path planning result in the global context.

The stochastic perturbation algorithm, an approach to break traps by adding random virtual forces, can randomly alter the robot's position and speed during the search process to increase the its diversity. The major steps are as follows:

3.1. Judgment that the robot is stuck in the local minimum point

When an algorithm iteration ends, the robot's distance from the target point is computed, and if it exceeds a predetermined threshold, the robot is perceived to have been captured in the local minimum point.

3.2. Construct the perturbation vector at random

A perturbation vector with random magnitude and orientation is created during each iteration. The location and speed of robot and can be modified by adopting this vector.

$$r = normrnd(mu, sigma, m, n) \quad (11)$$

The parameter *mu* stands for the mean value, the parameter sigma denotes the standard deviation, and $m \times n$ means the matrix size.

3.3. Position and velocity of robot with perturbation

Adding the randomly generated perturbation vectors to the robot position and velocity causes the robot to perform certain offsets. Meanwhile, the velocity scale and position range should be limited to avoid exceeding the search space.

3.4. The updated potential energy value

Calculating the new position and velocity of the robot, and the value of the objective function can produce a new potential energy value [10]. If the new value is lower than the historical best value, the new value will become a substitute for best value. Moreover, the robot's historical best value will also be updated if the new potential energy value is smaller than the robot's historical best value.

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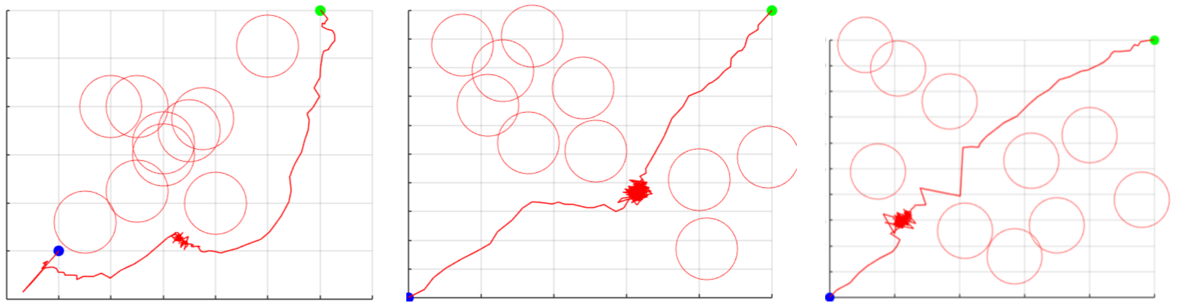
3.5. *Judgment of termination conditions*

If satisfying the set termination conditions, the search will be halted. Otherwise, return to step 2 and continue the Iteration search.

4. Analysis of experimental results

Numerous numerical modelling tests are carried out to verify the efficacy of the stochastic perturbation APF algorithm suggested in this article. As shown in Figure 3, the tests are carried out by employing the MATLAB software in a straightforward two-dimensional context. The goal point is a green point, the robot location is in red and blue point, and the red area denotes the field that repels obstacles.



(a) (b) (c)

Figure 4. Experimental results. Map of (a)-(c) is similar to that on Figure 3.

Figure 3 demonstrate the motion of a robot employing the conventional artificial potential field method in the same context. While in the Figure 4 the random perturbation is generated with the conventional artificial potential field method, which illustrates that the robot can effectively achieve the goal point and avoid the local minimum point by incorporating random perturbation after it reaches the local optimum.

According to research outcomes, the approach suggested in this article are able to prevent getting caught into the local optimal point and may identify the global optimum solution more quickly in a certain degree. Particularly, the suggested method in this paper has enhanced both the efficiency of the search and the precision of the end answer as compared to the conventional artificial potential field method. This implies that the stochastic perturbation algorithm can efficiently boost the search's diversity, assisting the and technique in avoiding the trap and spotting a superior answer.

5. Conclusion

This paper presents an improved algorithm to solve the problem of local optimal point in and called the stochastic perturbation artificial potential field method. As the robot moves through an end, the distance between the robot and the target point is always calculated. If the distance between the robot and the target point remains constant over a period of time, or if the stopping point oscillates, it is determined whether the robot has reached the target point at that point. If not, it is determined that the robot has fallen into a local optimum at this point. Once the determination is complete, a random perturbation is applied to the robot to cause it to jump out of the local optimum and continue navigating towards the target point. Where the local optimal point challenge of the APF algorithm is solved, and the algorithm's efficacy is confirmed by numerical simulation tests, with the assist of random perturbation.

There are still some problems with this algorithm, such as the difficulty in determining the direction of robot movement after adding random perturbations, resulting in a route that may not be optimal, and secondly, when the robot is moving in an end, there are some dynamic obstacles, and when the potential field of these obstacles changes from moment to moment, resulting in the difficulty in determining the size of the random perturbations. In future work, the end of the robot in the presence of dynamic obstacles will be taken into consideration and optimize the algorithm so that the robot can find the optimal route for obstacle avoidance faster and better.

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