Path planning of mobile robot based on improved artificial potential field method

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Abstract: Artificial potential field method is widely used in robot path planning because of its simplicity, efficiency and smooth path generation. In this paper, based on the introduction of the basic principle of the artificial potential field method, the limitations of the algorithm are analysed in depth, and improvement methods are summarized for these problems. Aiming at the problem that the target near the obstacle is unreachable in the traditional artificial potential field method, an improved repulsive force potential field function is used to introduce the distance between the robot and the target point into the potential field function, so that the potential field of the target position is minimized in the global potential field, so that the robot can successfully reach the target. Using the obstacle connection method, the robot can quickly get rid of the local minimum point, go out of the local minimum area, and complete the path planning. The simulation results show that the method is effective.

Keywords: Mobile robot, path planning, artificial potential field, local minima.

Introduction

The idea of a path planning approach is to make the robot move from its starting point towards a destination point, or goal, while avoiding obstacles on its way. Many algorithms for path planning have been studied and developed over the past few years (Lazarowska, 2019; Suwoyo, Abdurohman, et al., 2022) . The main methods of path planning for mobile robot can be divided into two categories artificial potential field (APF) approaches and artificial intelligence (Al) approaches (Suwoyo & Harris Kristanto, 2022). The main Al-based approaches for robot path planning are the genetic algorithm, the fuzzy control algorithm and the Artificial Neural Network. The computational complexity of these approaches limits real-time applications to

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only very simple cases, because their computation time increases exponentially with the number of robots and the complexity of the environment (Suwoyo, Hidayat, et al., 2022).

The classical Artificial Potential Field (APF) method consists of assigning an attractive artificial potential field to the destination point that attracts the robot, and a repelling artificial potential field to the obstacles that repel the robot. Being under the influence of these two combined potentials, the robot moves to its destination while avoiding the obstacles on its way. The way this algorithm works is that although the potentials are only artificial, they can generate an artificial force field which, in turn, combined with the robot's state and artificial dynamics can produce a virtual velocity and acceleration that are used as an instantaneous reference to control the robot's pose (Addya et al., 2019; Tan et al., 2023).

This method is particularly attractive because of its elegant mathematical analysis and simplicity. In 1986, Khatib first introduced the artificial potential field (APF) method. The method assigns a virtual potential to the target point, which attracts the robot as the distance increases, and for obstacles, a virtual potential is assigned that repels the robot more and more as the robot gets closer and closer to the obstacle. Globally, the robot moves toward the destination point while avoiding the obstacles along it s way (Yu et al., 2023). In the past decade this method has been studied extensively for autonomous mobile robot path planning by many researchers (Suwoyo, Thong, et al., 2022). Khosla and Volpe model the obstacles' potential as super quadrics. Siemiatkowska uses fluid diffusion equations to generate a trajectory. These methods are global and require the prior knowledge of the robot's environment (Vásconez et al., 2023). Local methods using APF are developed among others by Krogh and Khatib (Escobar-Naranjo et al., 2023). The classic APF method is adapted to mobile robots. This method is straightforward and does not require excessive computational power. It suffers however from certain drawbacks inherent to the classical APF method, especially oscillations and local minima. In previous studies, APF methods have been used to deal with mobile robot path planning in stationary environments, where targets and obstacles are all stationary. However, in many real-world implementations, the environments are dynamic. In this kind of application, the traditional APF is not applicable as it would cause inefficient path planning or generate a local minimum problem. Proposes one evolutionary artificial potential field in which both the vector of velocity and acceleration are considered. This method can be efficiently applied in a dynamic environment to avoid moving obstacles.

In this paper, based on the traditional artificial potential field, a new path planning algorithm for mobile robots is proposed to achieve real-time obstacle avoidance and path planning. The algorithm improves the artificial potential field function and solves the problem of unreachable targets near obstacles. Section 2 introduces the principle and limitation of the traditional artificial potential field method. In section 3, the improved artificial potential field method is introduced. Section 4 verifies the effectiveness of the method through simulation experiments (Siming et al., 2018).

Research Method

Improvement of artificial potential field method

In the traditional artificial potential field method (Li et al., 2021), the root cause of the local minimum problem is that when the robot is close to the target, the gravitational field decreases sharply and the repulsive force field increases continuously, making the robot unable to reach the target. In the improved artificial potential field function, by introducing the relative position of the target point and the robot (Lazarowska, 2019; Liu et al., 2022), the original repulsion field function is multiplied by a factor $(X - X_g)^n$, so that the repulsion force at the target position is 0, then the target point is still the global minimum point of the entire potential field. Keep the gravitational field function of the target point unchanged, and the repulsion field function of the corrected obstacle is:

$$U_{\text{rep}}(X) = \begin{cases} \frac{1}{2} k_{\text{rep}} \left(\frac{1}{X - X_0} - \frac{1}{\rho_0} \right)^2 (X - X_g)^n, & X - X_o \leqslant \rho_0 \\ 0, & X - X_o > \rho_0 \end{cases}, \tag{1}$$

Where: $0 < n \leq 1$, the repulsion force is:

$$F_{\text{rep}}(X) = -\nabla U_{\text{rep}}(X) = \begin{cases} F_{\text{rep}\,1} + F_{\text{rep}\,2}, & X - X_0 \leqslant \rho_0 \\ 0, & X - X_0 > \rho_0 \end{cases}, \tag{2}$$

Where

$$F_{\text{repl}} = k_{\text{rep}} \left(\frac{1}{X - X_0} - \frac{1}{\rho_0} \right) \frac{1}{(X - X_0)^2} \frac{\partial (X - X_0)}{\partial X} (X - X_g)^n, \tag{3}$$

$$F_{\text{rep}\,2} = -\frac{1}{2} k_{\text{rep}} \left(\frac{1}{X - X_0} - \frac{1}{\rho_0} \right)^2 \frac{\partial (X - X_g)^n}{\partial X}, \tag{4}$$

Where: the direction of F_{repl} is that the obstacle points to the robot, and the direction of $_{\text{rep}\,2}$ is that the robot points to the target point. Because $0 < n \leq 1$, when the robot approaches the target point, the repulsive force F_{repl} of obstacles near the target point tends to zero, and the robot can drive to the target point under the drive of $F_{\text{rep}\,2}$.

Obstacle connection method

The local minimum point will form a local point with zero resultant force or a local area close to zero in the artificial potential field, and the robot cannot walk out of this area. When the robot retreats out of the area, this paper considers connecting the obstacles in the area where the local minimum points are generated (Yang et al., 2022), so as to avoid the robot falling into the local minimum state again when re planning the path, as shown in Figure 4.

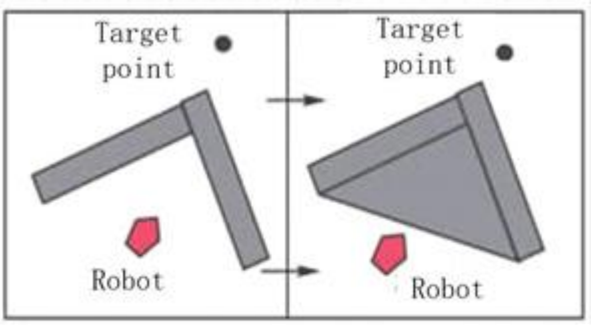

Figure 1 Schematic Diagram of Obstacle Connection Method

In this case, it is equivalent to the obstacle that the local minimum area is filled into a whole. The repulsive potential field of the filled area is:

$$U_{\text{local}}(X)=\begin{cases} k_{\text{local}}\dfrac{1}{(x-x_{\text{local}})^2}, & x-x_{\text{local}}\leqslant\rho_l \\ 0, & x-x_{\text{local}}>\rho_l \end{cases}, \tag{5}$$

Where: k_{local} is the proportional coefficient, which is the normal number; $x - x_{\text{local}}$ is the distance from the local minimum point when the robot retreats outside the local minimum area; p_l is the influence range of the local minimum area (Chen & Paul, 2022).

Result and Discussion

In this algorithm, the radius of the mobile robot is 44.5cm, the mass is 9.0kg, and the maximum linear speed of the robot is 500mm/s, and the maximum angular speed is 100deg/s. In different environments, the simulation diagrams of the traditional artificial potential field method and the improved artificial potential field method are shown in Figures 2 to 3.

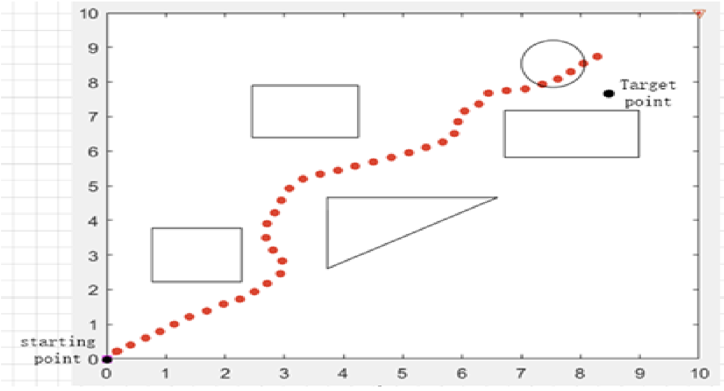

Figure 2 Simulation result before algorithm improvement

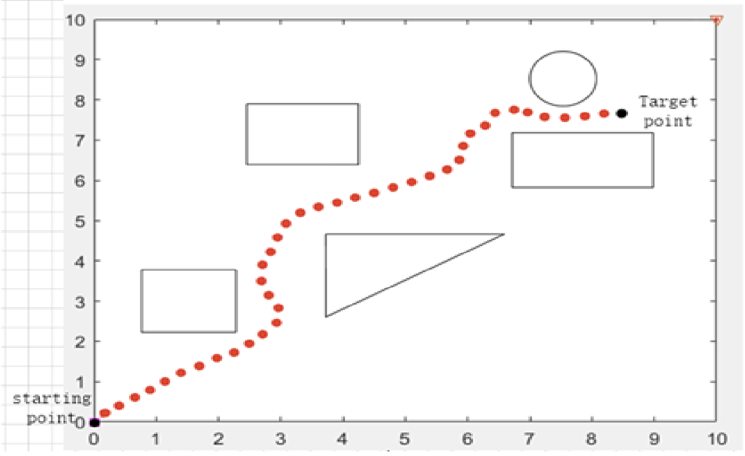

Figure 3 Simulation result after algorithm improvement

1. It can be seen from Figure 2 that when there are obstacles near the target point, the robot cannot reach the target point smoothly because the robot is in the repulsive force range when using the traditional artificial potential field method. As can be seen in Figure 3, with the improved repulsion potential field function, the robot can still reach the target smoothly even if there are obstacles near the target point.
2. It can be seen from Figure 4 that when a "U" shaped area appears in the environment, the robot will vibrate in this area. After using the obstacle connection method in this paper, as shown in Figure 5, the robot can get rid of the local minimum area after entering the "U" shaped area and reach the target smoothly.

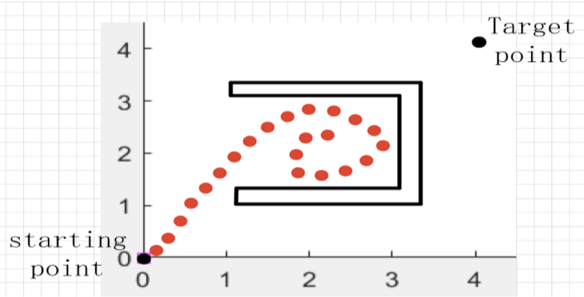

Figure 4 Simulation result after algorithm improvement

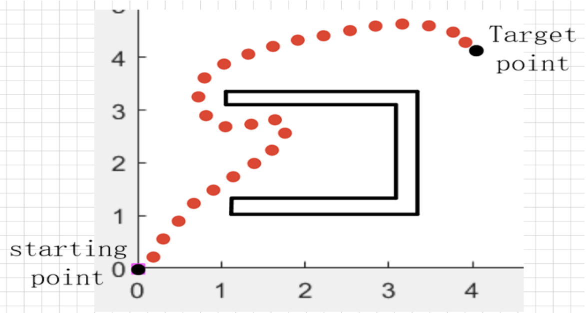

Figure 5 Simulation result after algorithm improvement

Conclusions

The path planning method based on artificial potential field algorithm is one of the important methods for mobile robot path planning. In this paper, based on the introduction of the basic principle of the artificial potential field method, the limitations of the algorithm are analyzed in depth, and improvement methods are summarized for these problems. Aiming at the problem that the target near the obstacle is unreachable in the traditional artificial potential field method, an improved repulsive force potential field function is used to introduce the distance between the robot and the target point into the potential field function, so that the potential field of the target position is minimized in the global potential field, so that the robot can successfully reach the target. Using the obstacle connection method, the robot can quickly get rid of the local minimum point, go out of the local minimum area, and complete the path planning. The simulation results show that the method is effective.

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