A Hybrid Path Planning Method for Mobile Robot Based on Artificial Potential Field Method

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Abstract. This paper proposes a hybrid path planning method based on artificial potential field method (APF) for mobile robot, which combines wall following method (WFM) and obstacles connecting method (OCM) for dealing with local minimum. The environment information is took into consideration to decide the escape direction of WFM. To ensure the success of escaping from local minimum, more reliable switching conditions are designed. OCM is applied to reduce the difficulty of path planning for complex workspace with concave obstacles. Simulation studies have been carried out to verify the validity of the proposed method.

Keywords: artificial potential field method, wall following method, escape direction, switching conditions, obstacles connecting method

1 Introduction

In recent years, mobile robot has been drawn much attention in various fields, such as military, rescue and inspection. Since the actual application scenarios are often complex, it puts forward high demands on the path navigation and collision avoidance strategy of mobile robot[1]-[3].

There have been plenty of researches on the path planning, the typical algorithms are Dijkstra[4], A*[5], RRTs[6] and artificial potential field method[7]. Dijkstra, A*, RRTs are global path planning methods, whose amount of calculation will increase dramatically as the map expands. Comparatively, the artificial potential field method (APF), which has the character of simplicity and low-time consumption, is more suitable for mobile robot real-time path planning. The basic idea of APF is to conduct the robot to move towards the goal by the attractive force, and avoid obstacles by the repulsive force. However, this method is prone to fall into the problem of local minimum, leading to the failure of reaching the target[9].

In order to further apply the APF in practice, the local minimum problem has been extensively studied[8]-[12]. In [8], a gradually expanding search range was proposed to detect the obstacles nearby, therefore the UAV can always move towards the low potential energy direction with no collision. In [10]-[11], a method combined the wall following method (WFM) with the APF was developed to escape from the local minimum. However, due to the insufficient utilization of the environment information, it may not choose the best escape direction, resulting in the extension of useless path. In[12], to prevent the mobile robot from being trapped by the obstacle groups, the obstacles connecting method (OCM) was employed to connect the obstacles into a whole.

Inspired by the results of [10]-[12], in this paper, we propose a hybrid path planning method based on the APF, combining the WFM and OCM. Once the mobile robot is trapped in the local minimum, WFM is utilized to escape from the trap. The environment information will be took into consideration to decide the escape direction. The switching conditions from WFM to AFP have been fully studied. For better path planning performance, the OCM is applied to prevent the mobile robot from dropping into the traps consisting of concave obstacles or multiple independent obstacles. The APF will be briefly described in Section 2. In Section 3, the schemes of dealing with local minimum are discussed. In Section 4, the simulation results are given.

2 The Traditional Artificial Field Method

For simplicity, we regard the mobile robot as the mass point, and its position in workspace is denoted by $\mathbf{p} = (x, y)$. In the same way, the position of goal is denoted by $\mathbf{p}_{goal} = (x_{goal}, y_{goal})$.

The attractive potential function is defined as:

$$\boldsymbol{U_{att}}(\mathbf{p}) = \frac{1}{2}\alpha\boldsymbol{\rho}^2(\mathbf{p}, \mathbf{p}_{goal}) \tag{1}$$

where α is a positive constant, $\boldsymbol{\rho}(\mathbf{p}, \mathbf{p}_{goal}) = \|\mathbf{p}_{goal} - \mathbf{p}\|$ represents the Euclidean distance between $\mathbf{p}$ and $\mathbf{p}_{goal}$.

The repulsive potential function takes the form[11]:

$$\boldsymbol{U_{rep}}(\mathbf{p}) = \begin{cases} \frac{1}{2}\beta(\frac{1}{\boldsymbol{\rho}(\mathbf{p}, \mathbf{p}_{obs})} - \frac{1}{\boldsymbol{\rho}_0})^2\boldsymbol{\rho}^2(\mathbf{p}, \mathbf{p}_{goal}) & \boldsymbol{\rho}(\mathbf{p}, \mathbf{p}_{obs}) < \boldsymbol{\rho}_0 \\ 0 & \boldsymbol{\rho}(\mathbf{p}, \mathbf{p}_{obs}) \geq \boldsymbol{\rho}_0 \end{cases} \tag{2}$$

where $\boldsymbol{\rho}_0$ is the maximum influence distance of obstacles, $\mathbf{p}_{obs} = (x_{obs}, y_{obs})$ denotes the closest point to the robot on the obstacle, $\boldsymbol{\rho}(\mathbf{p}, \mathbf{p}_{obs})$ represents the minimum distance between $\mathbf{p}$ and $\mathbf{p}_{obs}$.

Then, we can obtain the attractive force $\boldsymbol{F_{att}}(\mathbf{p})$ and repulsive force $\boldsymbol{F_{rep}}(\mathbf{p})$ by taking the negative gradient of the corresponding potential. Due to the limited space, it will not be presented here.

The resultant force on the robot can be expressed as:

$$\boldsymbol{F_{res}}(\mathbf{p}) = \boldsymbol{F_{att}}(\mathbf{p}) + \Sigma\boldsymbol{F_{rep}}(\mathbf{p}) \tag{3}$$

where $\Sigma\boldsymbol{F_{rep}}(\mathbf{p})$ is the sum of repulsive forces of all obstacles.

3 Schemes for Coping with Local Minimum

3.1 Escape Direction of Wall Following Method

When the robot is in the local minimum, the attractive force on it is equal to the sum of the repulsive forces. And we can see the phenomenon that the robot stops at a location or hovers around a small area. To judge whether the robot is trapped in the local minimum, we define the following condition:

$$\|\mathbf{p}(t) - \mathbf{p}(t - 2T)\| < \gamma \tag{4}$$

where $\mathbf{p}(t)$ denotes the current position of the robot, T is a cycle time, $\mathbf{p}(t-2T)$ represents the position in the last two cycles, γ is a distance threshold .

Once the robot drops into the local minimum, WFM will be applied to break the deadlock. Then robot can keep moving on along the direction of $\theta_{rep} \pm 90°$, until the switching conditions for converting to APF are satisfied, where θ_{rep} is the direction of the sum of repulsive forces. As to the local minimum generated by concave obstacle or multiple independent obstacles, different escape directions can lead to greatly different path planning results. Fig. 1 shows the results of path planning from (6,4) to (2,4) with different escape directions, in which the red arrows represent the direction of θ_{rep} at the local minimum. Since we have obtained the environment information in advance, we can specifically set the escape direction for the complex obstacles to enhance the success rate of path planning. When the robot is trapped in a concave obstacle, if the distance to the goal in the clockwise direction along the obstacle is closer, the escape direction will be set to $\theta_{rep} + 90°$. If the robot moves to the goal closer in the counterclockwise direction, the escape direction will be set to $\theta_{rep} - 90°$. While, if the robot is trapped outside the obstacle, it will get the opposite result. For general obstacles, the escape direction is $\theta_{rep} + 90°$ by default.

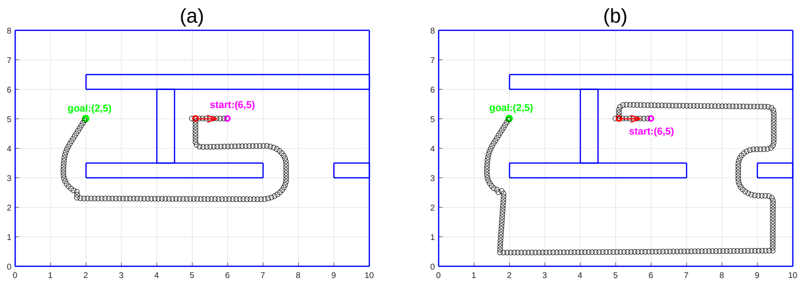

Fig. 1: The escape direction. (a)$\theta_{rep} - 90°$. (b)$\theta_{rep} + 90°$.

3.2 Switching Conditions from Wall Following Method to Artificial Potential Field Method

After escaping from the local minimum using WFM, the movement pattern needs to be converted to APF to approach the goal. The switching conditions from WFM to APF play a key role in the path planning scheme. If the movement pattern is converted to APF too late, the robot will miss the goal, or if the conversion is too early, the robot will remain trapped in the local minimum.

In [11], the robot needs to go a long way around the edge of the obstacles to meet the switching conditions if it is trapped by a local minimum, which is not suitable for practical application. Based on the switching conditions in [11], we have added new switching conditions to improve the performance of path planning:

$$(|\Delta\theta_{att-trap}| > 90^\circ \bigcup |\Delta\theta_{att}| > \theta) \bigcap \theta_{min} < \theta_{res} < \theta_{max} \tag{5}$$

where $\Delta\theta_{att-trap} = \theta_{att} - \theta_{trap}$ and $0 \leq \Delta\theta_{att-trap} \leq 180^\circ$, θ_{att} is the angle of attractive force, θ_{trap} is the angle of the vector that points to the local minimum from the current position, $\Delta\theta_{att}$ is the angle increment of attractive force since the movement pattern is converted to WFM, θ_{res} is the angle of resultant force, θ, θ_{min} and θ_{max} are angle thresholds, the values of which are shown in Table 1. The first two conditions ensure that the robot has been away for a long enough distance in the WFM mode. The last condition is used to confirm the robot has been escaped from the local minimum successfully. When it is satisfied, the component of the resultant force on the robot is greater in the direction of attractive force, then the robot can move towards the goal under the control of the resultant force. The experiment results compared with the method in [11] are showed in Fig. 2.

Table 1: The values of θ_{max} and θ_{min}

	$\lvert\theta_{att} - \theta_{trap}\rvert < 180^\circ$	$\lvert\theta_{att} - \theta_{trap}\rvert > 180^\circ$
$\theta_{att} < \theta_{trap}$	$\theta_{min} = \theta_{att} - 90^\circ$ $\theta_{max} = \theta_{att} + \lvert\theta_{att} - \theta_{trap}\rvert/2$	$\theta_{min} = \theta_{att} - (180^\circ - \lvert\theta_{att} - \theta_{trap}\rvert)/2$ $\theta_{max} = \theta_{att} + 90^\circ$
$\theta_{att} > \theta_{trap}$	$\theta_{min} = \theta_{att} - \lvert\theta_{att} - \theta_{trap}\rvert/2$ $\theta_{max} = \theta_{att} + 90^\circ$	$\theta_{min} = \theta_{att} - 90^\circ$ $\theta_{max} = \theta_{att} + (180^\circ - \lvert\theta_{att} - \theta_{trap}\rvert)/2$

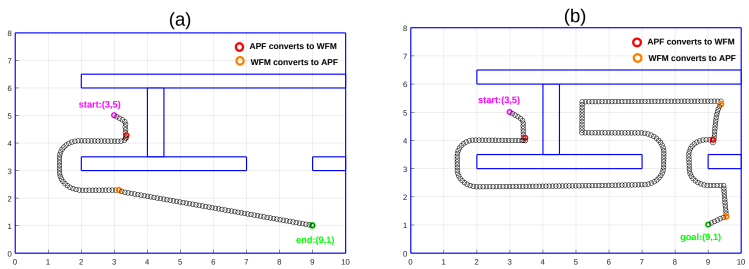

Fig. 2: (a) Switching conditions in proposed method. (b) Switching conditions in [11].

3.3 Obstacles Connecting Method

Local minimum is easily formed around the concave obstacles and obstacle groups. When the robot needs to go through those obstacles to approach the goal, it will spend extra useless costs to bypass the obstacles or escape from the local minimum. According to the environment information, we can connect the concave obstacles and obstacle groups into convex obstacles which can greatly reduce the difficulty of path planning and improve the path planning performance. Fig. 3 shows the path planning results of whether the obstacle is connected.

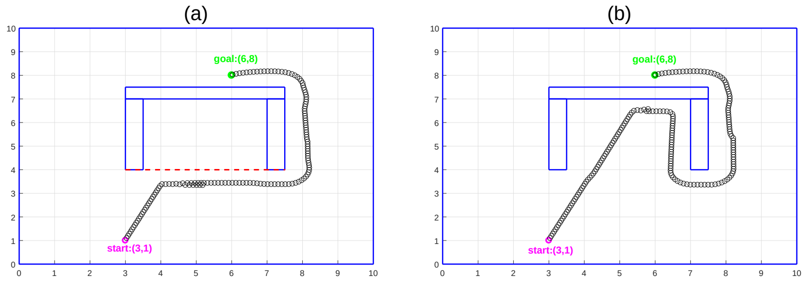

Fig. 3: (a) Connecting obstacles. (b) No disposal.

4 Simulation Results

To verify the rationality and superiority of the proposed method, we carry out a simulation experiment and compare with the method in [11]. The workspace is in the size of the $10m \times 8m$ with concave and convex obstacles. The parameters are set as $\alpha = 1$, $\beta = 0.1$, $\boldsymbol{\rho}_0 = 0.8$, $\gamma = 0.08$, $\theta = 90°$. Suppose the robot is moving at a constant speed of $0.1m/s$, and the resultant force on it only determines the direction of its motion. The starting position and the goal are set to $(9.7, 2)$ and $(1, 7)$, respectively.

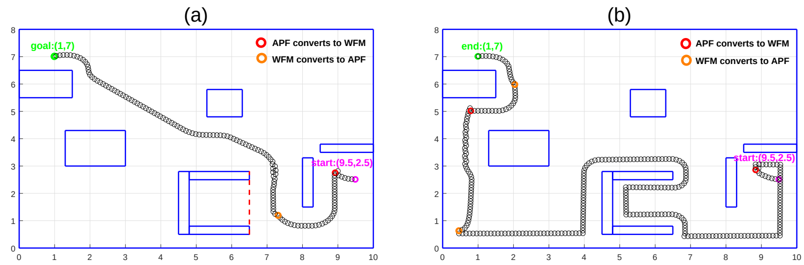

Fig. 4: (a) The proposed method. (b) The method in [11].

The comparative experiment results are shown in Fig. 4. It is obvious that the length of the path in (a) is shorter than that in (b). When the robot first falls into the local minimum generated by the concave obstacle, it chooses the escape direction of $\theta_{rep} - 90°$ in (a) and then easily gets away from the trap. Due to the next concave obstacle is connected into a convex obstacle that reduces the difficulty of path planning, the robot successfully passes through it and reaches the goal at last. However, in (b), the robot chooses the escape direction of $\theta_{rep} + 90°$. It goes a long way under the WFM mode around the boundary of the obstacles before the APF converting conditions are satisfied. Besides, there are many sharp turns in the path, which makes it difficult for the robot to track in practice. It can be seen from the simulation results that the proposed method is effective, which can plan a smoother and more efficient path for mobile robot.

5 Conclusion

In this research, WFM and OCM are employed to deal with the local minimum. The environment information is took into account to choose the escape direction of WFM. New switching conditions from WFM to APF are developed for better path planning. OCM is applied to reduce path planning difficulty and smooth the path, by connecting the concave obstacles into convex obstacles. Simulation results show that the proposed hybrid path planning method can plan a more reasonable path for mobile robot, witch is shorter and smoother.

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