Research on Path Planning Algorithm of Bidirectional Rapidly Exploring Random Tree Improved by Artificial Potential Field

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Abstract: Aiming at the defects of path planning in rapidly exploring random tree (RRT) algorithm, such as low efficiency, strong randomness and slow convergence rate, a new algorithm based on artificial potential field was proposed in this paper. The algorithm used the scheme of bidirectional growth of exploration tree to make two growth trees explore and expand outwards from the starting point and the end point at the same time to accelerate the convergence speed of the algorithm. In the early stage, growth pretreatment was added to make the two growing trees take their respective endpoints as the target points and pass through the obstacle-free area rapidly at one time. Artificial potential field method was used to modify the growth tree touching the obstacle and guide the path to grow towards the end. The adaptive change probability was used to select different target points as the growth directions in different periods with different probabilities to accelerate the meeting of two growing trees. After a lot of simulation experiments and data analysis, the improved bidirectional RRT algorithm has higher search efficiency, better growth path and fewer sampling points.

1. Introduction

With the continuous development of the robotics field, mobile robots have been closely related to human life and have been widely used in many fields [1-2]. As one of the core issues in the field of mobile robot research, path planning is an important foundation for mobile robots to complete various tasks [3]. The so-called path planning is to allow the mobile robot to find a safe, collision-free and optimal or suboptimal path from the start point to the end point under a prescribed known environment [4]. The rapidly-exploring random tree algorithm [5-6] is a path planning algorithm based on random sampling. The RRT path planning algorithm has the advantages of no need to model or preprocess the space, strong search and avoidance capabilities, and quick exploration of unknown areas on the map. However, it also has the disadvantages of blindness, strong randomness, and poor stability in search [7].

This article improves the RRT algorithm in three aspects. First, the improved algorithm in this paper uses the two-way RRT algorithm, and adds growth pre-processing in the early stage, so that the two growing trees take their respective end points as the target point, and quickly pass through the obstacle-free area at one time; second, use the artificial potential field method to solve the problem. The growth tree that touches the obstacle is corrected to guide the path to grow toward the end; third, use the adaptive change probability to select different target points as the growth direction at different times with different probabilities to speed up the encounter of two growing trees. Through experimental analysis,
the improved algorithm in this paper has fewer sampling points, higher search efficiency and better growth path.

2. RRT algorithm and artificial potential field method

2.1. RRT algorithm

The classical RRT path planning algorithm is an incremental sampling search algorithm. Its main idea is to use the starting point of the path as the root node of the tree. New nodes are set by random sampling in the space, and the random tree is continuously expanded. Until the random tree is extended to the step detection range of the target point, a feasible path is generated. The main steps are as follows:

1. Set the starting point as the root node $X_{\text{start}}$ of the random tree in the known map.

2. Generate a random sampling point $X_{\text{rand}}$, traverse all nodes of the random tree and find the node $X_{\text{closest}}$ closest to $X_{\text{rand}}$.

3. Judge whether $X_{\text{rand}}$ is within the step size limit of node $X_{\text{closest}}$, otherwise calculate the middle point $X_{\text{new}}$ to replace $X_{\text{rand}}$.

4. Collision detection is performed on $X_{\text{new}}$ and $X_{\text{closest}}$ to determine whether there is an obstacle between them.

5. If the above conditions are met, add $X_{\text{new}}$ to the random tree and set $X_{\text{closest}}$ as the parent node of $X_{\text{new}}$.

6. Judge whether $X_{\text{new}}$ is within the step limit of the end point, and perform collision detection between the two.

7. If the above conditions are met, $X_{\text{new}}$ is set as the parent node of the end point, and the end point is added to the random tree, and the parent node is searched backward from the end point to plan a feasible path from the start point to the end point. Otherwise, repeat steps (2) ~ (6) until the conditions are met.

The single growth process of a new node in the RRT algorithm is shown in Figure 1.

![Figure 1. Single growth of a new node in a random tree](image)

Where $X_{\text{new}}$ is a new node generated under the limit of the basic step length $p$, obstacle is an obstacle, and $X_{\text{goal}}$ is the target end point.

The two-way RRT algorithm is based on the classic RRT algorithm and then adds a random exploration tree. The two growing trees explore and expand from the starting point and the end point respectively, until the algorithm converges when the two trees meet. This improvement has been To a certain extent, the exploration strategy improved the operating efficiency of RRT. Due to its random sampling characteristics, the RRT algorithm can effectively avoid falling into a local optimum when searching for a path, and has a strong ability to explore unknown spaces. However, the blindness of its search results in a planned path that is often not the optimal solution and is relatively stable. Poor, the algorithm is a path planning algorithm with complete probability rather than optimal.

2.2. Artificial potential field method

Artificial potential field method is a virtual force field method proposed by Oussama Khatib. The basic idea is to abstract the map environment around the mobile robot as a virtual force field. A gravitational
potential field is generated at the target end to attract the mobile robot to move to it. At the same time, the surrounding obstacles generate a repulsive potential field, which generates a certain repulsive force to the mobile robot. To make it avoid obstacles, the magnitude of attraction and repulsion changes with the position of the mobile robot. The gravitational potential function and gravitational function in the artificial potential field can be represented by functions (1) and (2) respectively:

\[ U_{\text{attr}}(X) = \frac{1}{2} K_a (X - X_{\text{goal}})^2 \]  

(1)

\[ F_{\text{attr}}(X) = -K_a (X - X_{\text{goal}}) \]  

(2)

In equations (1) and (2), \( X \) is the current coordinates of the mobile robot, \( X_{\text{goal}} \) is the end point coordinates, and \( K_a \) is the gravitational gain coefficient.

The repulsion potential function and the repulsion function in the artificial potential field can be represented by functions (3) and (4) respectively:

\[ U_{\text{rep}}(X) = \begin{cases} 
\frac{1}{2} K_r \left( \frac{1}{\rho(X)} - \frac{1}{d_0} \right)^2, & \rho(X) < d_0 \\
0, & \rho(X) > d_0 
\end{cases} \]  

(3)

\[ F_{\text{rep}}(X) = \begin{cases} 
K_r \left( \frac{1}{\rho(X)} - \frac{1}{d_0} \right) - \frac{1}{\rho(X)^2} \frac{\partial \rho(X)}{\partial X}, & \rho(X) < d_0 \\
0, & \rho(X) > d_0 
\end{cases} \]  

(4)

In equations (3) and (4), \( X \) is the current coordinates of the mobile robot, \( \rho(X) \) is the distance between the current coordinates of the mobile robot and the nearest obstacle, \( d_0 \) is the distance threshold between the mobile robot and surrounding obstacles, and \( K_r \) is Repulsion gain coefficient.

The entire artificial potential field is composed of the superposition of the gravitational field and the repulsive force field. The total force received by the mobile robot in it is the sum of the gravitational force \( F_{\text{attr}} \) applied to the target end point and the repulsive force \( F_{\text{rep}} \) applied to it by nearby obstacles, as shown in formula (5) Shown.

\[ F_{\text{total}}(X) = F_{\text{attr}}(X) + F_{\text{rep}}(X) \]  

(5)

The mobile robot moves to the end point and avoids obstacles while avoiding obstacles under the combined force of gravitation and repulsion. The path obtained is generally smooth and safe. But its shortcomings are also obvious. When there is a trap area in the map, the mobile robot will fall into the local optimal solution and cannot jump out; when the end point is near the obstacle, the path will oscillate near the end point and cannot reach the end point.

3. Improve algorithm

This article combines the RRT algorithm with the artificial potential field method and further improves it. In the early stage of path growth, the two growing trees are made to face their respective end points for collision detection, and quickly pass through the obstacle-free area at one time; add an adaptive target bias algorithm, not a single end point as the target bias point; combined with artificial potential field Method, when the growing tree encounters an obstacle, the artificial potential field is used to guide the growth.

3.1. Growth pretreatment

Due to the strong randomness of the RRT algorithm, many redundant paths will be generated in the non-obstacle area during the path growth process, causing some unnecessary searches and calculations and slowing the convergence speed. Therefore, a pre-processing is performed on the random exploration tree in the early stage of its path growth. First, the root nodes of the two growing trees are targeted at their respective end points, and a collision detection is performed respectively, and the obstacle is stopped; then a node to be grown at a suitable distance from the obstacle is calculated to avoid the node
to be grown from the obstacle. When the object is too close, it will collide with the obstacle during the next growth; finally, connect the two root nodes and the respective nodes to be grown, and initially obtain two growing trees. Under special circumstances, if there are no obstacles in the straight line connecting the start point and the end point, the final path can be obtained directly. The schematic diagram of the growth pretreatment of the random tree is shown in Figure 2.

In this way, the number of random sampling points can be reduced to a certain extent and the path convergence speed can be accelerated, so that the random growth tree can quickly pass through the non-obstacle area in the early stage of path growth at one time, reducing unnecessary growth and calculation.

3.2. Bidirectional adaptive target bias

In the Goal-biasing RRT algorithm, the target end point is selected as the sampling point with a certain probability every random sampling, and the growth tree is guided to grow to the end point, which solves the problem of strong randomness of the RRT algorithm to a certain extent. However, the probability of the Goal-biasing RRT algorithm selecting the target point each time and the coordinate position of the target point are fixed. When two growing trees are about to meet, if the respective endpoints are still used as random sampling points, the final convergence speed may be affected.

Therefore, this paper proposes a two-way adaptive Goal-biasing algorithm. First, set a fixed probability \( P_0 \), and each sampling probability of a random sampling point is a random value \( P \) between 0 and 1; when \( P_0 < P < 1 \), in the map randomly generate sampling points in \( X_{\text{rand}} \) to guide random tree growth; when \( 0 < P < P_0 \), calculate the Euclidean distance between the last growth node of the growth tree \( T_1 \) and the last growth node of the growth tree \( T_2 \), and divide this value by the map start The value of the Euclidean distance between the start point and the end point is obtained, and a value \( P_{\text{var}} \) that changes with the growth of two growing trees is obtained. The calculation formula is as follows:

\[
P_{\text{var}} = \frac{\| X_{T1\text{end}} - X_{T2\text{end}} \|}{\| X_{\text{start}} - X_{\text{goal}} \|} \tag{6}
\]

In formula (6), \( X_{T1\text{end}} \) and \( X_{T2\text{end}} \) are the last growth nodes of the growth trees \( T_1 \) and \( T_2 \), and \( X_{\text{start}} \) and \( X_{\text{goal}} \) are the start and end points of the map, respectively. Generally, \( P_{\text{var}} \) is a value greater than 0 and less than 1. If there is a special case greater than 1, you can convert it to \( 1/P_{\text{var}} \) or leave it alone, which has no effect on the algorithm in this paper. When \( P_0 < P < P_{\text{var}} \), the last growth node of the growth tree is selected to guide another growth tree to grow; when \( 0 < P < P_0 P_{\text{var}} \), the target end point \( X_{\text{start}} \) or \( X_{\text{goal}} \) of the growth tree is selected as the sampling point to guide its growth.

In the early stage of path planning, if the two growing trees are far apart, the target bias probability will choose the target destination more to guide the growing tree to grow; as the growing trees grow...
closer to each other, the target bias probability gradually chooses the other. The last growth node of the growing tree guides its growth, which can speed up the final convergence speed of the two growing trees.

3.3. Artificial Potential Field Method Guides Path Growth

In the process of random sampling points to guide the growth tree outward expansion, the generated node to be grown may fall into the obstacle area. For the RRT algorithm, the idea is to remove the node and then randomly sample again. However, after re-random sampling, the newly generated nodes to be grown may still fall into obstacles or cannot move away from obstacles and approach the target point, which consumes a lot of time and calculation.

The gravitation and repulsion ideas in the artificial potential field method are integrated into the RRT algorithm, and the node $X_{new}$ to be grown is calculated from the random sampling point $X_{rand}$. The growth node $X_{new}$ and the nearest tree node $X_{closest}$ on the growth tree are detected for collision. If an obstacle is detected, the artificial potential field method is used to guide the path growth of the growing tree. The target end point exerts a gravitational force on the nearest tree node $X_{closest}$, calculates the coordinate $X_{obstacle}$ of the obstacle point closest to $X_{closest}$, and the nearest obstacle point exerts a repulsive force on the tree node $X_{closest}$. The tree node $X_{closest}$ bypasses the obstacle under the combined force of gravity and repulsion. Target end growth. The schematic diagram of the growth of new nodes improved by the artificial potential field method is shown in Figure 3.

![Figure 3. Diagram of new node growth improved by artificial potential field method](image)

When the new node generated by random sampling fails the collision detection, the artificial potential field method is used to improve the generation method of the new node, which can make the growth tree grow smoothly along the edge of the obstacle to the target point, especially when passing through a narrow channel. Effectively avoid the next growth of the new node from falling into the obstacle again, greatly improving the convergence speed of the two growing trees. Among them, the force of gravity on the nearest tree node can be expressed as:

$$F_{att} = p \cdot k_1 \frac{X_{goal} - X_{closest}}{||X_{goal} - X_{closest}||}$$

The force of the repulsive force on the nearest tree node can be expressed as:

$$F_{rep} = p \cdot k_2 \frac{X_{closest} - X_{obstacle}}{||X_{closest} - X_{obstacle}||}$$

Therefore, the new node generation formula improved by the artificial potential field method is:

$$X_{new} = X_{closest} + F_{att} + F_{rep} = X_{closest} + p(k_1 \frac{X_{goal} - X_{closest}}{||X_{goal} - X_{closest}||} + k_2 \frac{X_{closest} - X_{obstacle}}{||X_{closest} - X_{obstacle}||})$$

In formulas (7) ~ (9), $p$ is the basic step length of a single growth of the growing tree, and $k_1$ and $k_2$ are the gravitational coefficient and the repulsion coefficient, respectively.
4. Experimental results and analysis

In order to verify the effectiveness of the improved algorithm in this paper, the improved algorithm in this paper is compared and analyzed with artificial potential field method, RRT algorithm, and two-way target biased RRT algorithm in two map environments of general complex environment and narrow channel trap environment. The simulation experiment was implemented in the Windows 10 environment using the compiler tool MATLAB R2020a, running on a notebook computer, the processor was AMD (Ryzen 7) 2.90 Ghz, and the memory was 16 G. Set the map environment size to 500×500, the starting point coordinates are (10, 490), the ending point coordinates are (490, 10), the basic step length p = 10, the number of experiments for each algorithm is 20 times, and the mobile robot is assumed to be an ideal dot shape.

The simulation results on the general complex environment map are shown in Figure 4 and Table 1.

![Simulation results](image)

**Figure 4. Simulation performance of the four algorithms in general complex environment**

| Algorithm                      | Average number of iterations | Average number of waypoints | Average path length   | Average planning time/s |
|-------------------------------|------------------------------|-----------------------------|-----------------------|------------------------|
| RRT algorithm                 | 2208.3                       | 107.9                       | 1063.358              | 11.838                 |
| Artificial potential field method | --                           | --                          | --                    | --                     |

Table 1. Simulation results of four algorithms in general complex environment
Bidirectional target biased RRT algorithm & 149.3 & 88.9 & 883.756 & 0.305 \\
Improve algorithm & 59.4 & 46.9 & 797.381 & 0.116 \\

Analyzing Figure 4 and Table 1, in a general complex environment, the RRT algorithm generates a large number of random tree nodes in the map due to its strong randomness and purposeless search, which consumes a lot of calculation time, and the final path is more tortuous; artificial potential field The path generated by the method is relatively smooth, but it is easy to fall into the local optimum and it is difficult to jump out; the bidirectional target bias RRT algorithm due to its bidirectional growth characteristics and growth toward the target point with a certain probability, reduces the number of random tree nodes to a certain extent And calculation time, but its growth direction is still unstable, and the obstacle avoidance effect is not obvious. The improved algorithm in this paper is better than the above three algorithms in all indicators. Compared with the bidirectional target biased RRT algorithm, the average number of iterations is reduced by 60.2%, the average number of path points is reduced by 47.2%, the average path length is reduced by 9.8%, and the average planning The time is reduced by 62%.

The simulation results in the narrow channel trap environment map are shown in Figure 5 and Table 2.
Table 2. Simulation results of four algorithms in narrow channel trap environment

| Algorithm                        | Average number of iterations | Average number of waypoints | Average path length | Average planning time/s |
|----------------------------------|------------------------------|-----------------------------|--------------------|------------------------|
| RRT algorithm                    | 2414.6                       | 104.4                       | 1023.195           | 14.424                 |
| Artificial potential field method| --                           | --                          | --                 | --                     |
| Bidirectional target biased RRT algorithm | 1514.6                       | 103.4                       | 1021.832           | 5.47                   |
| Improve algorithm                | 80.4                         | 33.6                        | 884.952            | 0.145                  |

Analyzing Figure 5 and Table 2, in the narrow channel trap environment map, the path planned by the artificial potential field method falls into the local optimum and cannot reach the end; due to the narrow passage through the obstacle and the trap environment, the two-way target bias RRT Both the algorithm and the classic RRT algorithm need to spend a lot of sampling points and calculation time to pass through obstacles. The improved algorithm in this paper uses the growth pre-processing step in the environment map to effectively reduce the number of nodes in the early stage of path growth. In a narrow channel environment, the artificial potential field method is used to guide those who have not passed the collision detection. The node grows, the growth advantage is obvious, and the path growth efficiency is greatly improved; the adaptive target bias algorithm is used to overcome the defect that the artificial potential field method cannot pass through the trap area, and accelerate the encounter of two growing trees. Compared with the bidirectional target-biased RRT algorithm, the average number of iterations of the improved algorithm in this paper is reduced by 94.7%, the average number of path points is reduced by 67.5%, the average path length is reduced by 13.4%, and the average planning time is reduced by 97.3%.

5. Conclusions
In this paper, in view of the lack of purpose of path growth and slow convergence in the RRT algorithm, the growth pre-processing algorithm is added in the early stage of path planning, which reduces unnecessary path growth calculations and improves efficiency; for the growth of two growing trees The direction adds a two-way adaptive Goal-biasing algorithm, which selects different target points as the growth direction with different probabilities during different periods of the path growth, which speeds up the path convergence speed; borrowing the idea of artificial potential field method to improve the growth tree after touching obstacles The growth method improves the growth efficiency and avoids invalid growth again, especially in the narrow channel environment, the growth efficiency is significantly improved.

According to the simulation experiment, the improved algorithm in this paper has the advantages of less randomness, faster convergence, fewer path nodes required, and stronger obstacle avoidance ability, but the final path generated is not smooth enough, and there is still room for improvement.

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References
[1] Huo F.C., Chi J., Huang Z.J. (2018) Overview of path planning algorithms for mobile robots. Journal of Jilin University (Information Science Edition), 36(6): 639-647.
[2] Tzafestas, Spyros G. (2018) Mobile Robot Control and Navigation:A Global Overview. Journal of Intelligent & Robotic Systems, 91(1):35-58.
[3] Wang X.W. (2018) Research on path planning strategy of indoor autonomous navigation wheeled robot. Hefei: Hefei University of Technology.

[4] LaValle S.M. (2006) Planning Algorithms. Cambridge University Press, Cambridge.

[5] Situ H.j., Lei H.B., Zhuang C.G. (2021) RRT path planning algorithm based on artificial potential field guidance in dynamic environment. Computer Application Research, 38(03): 714-717+724.

[6] Liu C.J., Han J.Q., An K. (2017) RoboCup robot dynamic path planning based on improved RRT algorithm. Robot, 39(1): 8-15.

[7] Xu B.C., Yan H. (2020) An improved bidirectional rapid-exploring random tree algorithm. Science Technology and Engineering, 20(19): 7765-7771.