Proceedings of the 2023 International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/10/20230170

Path planning algorithm based on Improved Artificial Potential Field

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Abstract. The domain of research and development concerning mobile robot obstacle avoidance continues to remain an active area of interest. Artificial potential fields (APF) are a common and effective method for obstacle avoidance path planning, where the robot is guided to the target location by a simulated environmental potential field. Traditional artificial potential field methods tend to trap robots in local minima, impeding their ability to reach the goal. This research endeavours to introduce a new approach, the Improved Artificial Potential Field (IAPF) algorithm, which incorporates the A-star method in constructing the artificial potential field. This technique more effectively addresses the issue of path planning for mobile robots, thereby avoiding local minimum solutions. Through simulation experiments in different scenarios, the feasibility of the IAPF algorithm of this paper is verified. The results show that, compared with the traditional APF method, the IAPF algorithm can solve problem of local minimum and plan a sensible path.

Keywords: path planning, A-star, obstacle avoidance, artificial potential field.

1. Introduction

The advent of robot automation has resulted in the widespread application of mobile robots in various fields such as manufacturing, logistics, distribution, and medical care. However, the robot needs to avoid obstacles while automatically planning its path during its tasks, which requires specific method. The APF method is a commonly used robot obstacle avoidance method. It was first proposed by Khatib in 1986 and applied to the collision avoidance problem of the manipulator. The fundamental principle underlying the APF method involves constructing a potential field that reflects the environment in which a robot operates. This potential field affects the mobile robot, allowing it to be pulled towards its target position by a gravitational field while being repelled by the obstacle's repulsion field. The APF method enables a mobile robot to move towards the target point by constructing a potential field based on the environment. However, the traditional method has a tendency to get trapped in local minimum solutions, which restricts the robot's ability to reach the desired target and hinders its practical applications.

For the local minimum problem, Scholars have proposed many improved methods for the minimum point problem, such as randomized escape [1], heuristic search [2], harmonic potential field [3], simulated annealing [4], semi-landmarking [5], fuzzy artificial potential field [6], extremal Optimization [7], wall following [8], virtual flow [9] and so on. Their center ideas are treating the moving trajectory of the robot as a state sequence or replacing the binary logic operation in the traditional method with other operations. These methods are able to solve the local minimum question to a certain extent, but

DOI: 10.54254/2755-2721/10/20230170

most of these methods are complex and computationally intensive, which is not conducive to real-time update.

Therefore, this study aims to propose an IAPF algorithm for mobile robot path planning. The IAPF algorithm introduces the A-star technique when constructing the potential field, which can better avoid the emergence of local optimal solutions.

2. Artificial potential field

If a particle in any position in a space area, by the size and direction are determined by the single value of the force, then the region is called the force field[10], the force field on the particle force F writing space position of single value differentiable function[11] :

$$\begin{cases} F_x = F_x(x, y, z) \\ F_y = F_y(x, y, z) \\ F_z = F_z(x, y, z) \end{cases} \tag{1}$$

If there is a single-valued function $U = (x, y, z)$, its gradient is exactly equal to the force F in (1), the following equation holds [11]:

$$F_x = \frac{\partial U}{\partial x}, F_y = \frac{\partial U}{\partial y}, F_z = \frac{\partial U}{\partial z} \text{ or } F = \text{gradU} \tag{2}$$

Then this special force field in (2) is called the force field, also known as the conservative force field, and U is called the potential function.

The APF method entails establishing an APF for the robot's operational environment. This field is created by superimposing the gravitational field of the target location with the repulsive field of the obstacles [12]. Simply put, the APF comprises attractive and repulsive forces that steer the robot towards the target position, while simultaneously avoiding obstacles. The potential field is expressed mathematically as follows:

$$U = U_{att} + U_{rep} \tag{3}$$

In the (3): The attractive potential field is represented by U_{att}, while the repulsive potential field is represented by U_{rep}.

The APF methodology entails devising an abstract potential field for the robot's workspace, comprised of the superimposition of the attractive gravitational field of the target location and the repulsive field of obstacles. This APF can be mathematically represented as a function, and the gravitational and repulsive forces can be defined as the negative gradients of their respective fields. By using the spatial dynamics equation and the Lagrange equation, the force F acting on the robot due to the APF can be obtained:

$$F = F_{att} + F_{rep} \tag{4}$$

In the (4): F_{att} is the attraction of the target position to the robot, F_{rep} is the repulsion of the obstacle to the robot.

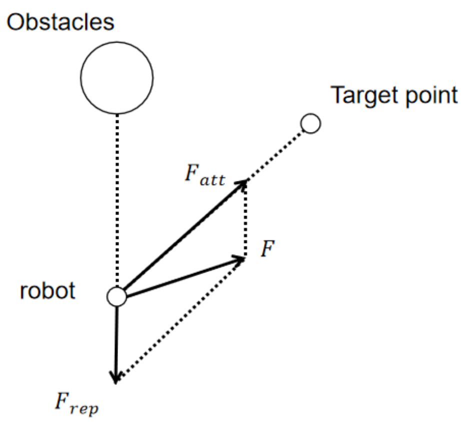

Figure 1. Force analysis of robot in APF.

Figure 1 gives a clear picture of the specific force analysis of the robot.

2.1. Gravitational field

The position of the robot in the workspace is defined as $X = (x, y)^T$, the gravitational potential function defined as [13]:

$$U_{att} = \frac{1}{2}k\left(X - X_g\right)^2 \tag{5}$$

The gravitational field that exists between the robot and the destination is mathematically represented by Equation (5), where the constant 'k' indicates the intensity of the gravitational potential field, X denotes the position vector of the robot, and X_g signifies the target position within the potential field. The attractive force that guides the robot towards the target is modeled by the negative gradient of the target potential function [14]:

$$F_{att} = -grad(U_{att}) = -k\left(X - X_g\right) = k\left(X_g - X\right) \tag{6}$$

2.2. Repulsion field

Khatib utilized a function called "Force Inducing an Artificial Repulsion from the Surface" as the repulsion potential function [15]:

$$U_{rep} = \begin{cases} \frac{1}{2}\eta\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 & ,\rho \le \rho_0 \\ 0\ , & \rho > \rho_0 \end{cases} \tag{7}$$

Equation (7) defines the repulsive force field of the obstacle as U_{rep}. The potential field constant for repulsive force, represented by η, is a positive value. The distance between the robot and an obstacle in space position is denoted by ρ, and the parameter ρ_0 indicates the maximum range of influence that a single obstacle can exert.

If the distance between the robot and an obstacle is less than or equal to ρ_0, the repulsive potential field will impact the robot's movement. Consequently, the repulsive force on the robot can be derived by computing the negative gradient of the repulsive potential function. Conversely, if the distance exceeds ρ_0, the repulsive potential field will have no effect on the robot's motion. [14]:

$$F_{rep} = -grad(U_{rep}) = \begin{cases} \eta\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2}\frac{\partial\rho}{\partial X} & ,\rho \le \rho_0 \\ 0\ , & \rho > \rho_0 \end{cases} \tag{8}$$

In the formula: $\frac{\partial\rho}{\partial X} = (\frac{\partial\rho}{\partial X}\ \frac{\partial\rho}{\partial Y})^T$

Of course, other functions can also be used, but it must be ensured that the functions used, and their derivatives are continuous. The above only considers the control force of a single obstacle on the robot. For multiple obstacles, the repulsive potential field of multiple obstacles can be obtained by superposition of potential fields.

At this point, the total potential field U can be expressed as [16,17]:

$$U = U_{att} + \sum U_{repi} \tag{9}$$

The resultant force of gravity and repulsion is:

$$F = F_{att} + \sum F_{repi} \tag{10}$$

2.3. The problem of APF

The main problem of APF in generating path is prone to local minima. The local minimum point means that the lowest point of potential energy encountered by the robot in the APF is not the global lowest point, but a local lowest point. This situation will cause the robot to wander back and forth near the local lowest point that cannot reach the target position, and cannot find the global lowest point or target position. This is because, as the robot approaches the target or obstacle, the gradient in the potential field becomes more and more gentle, and the robot is prone to local minima and cannot cross the potential peak [18].

3. A-star algorithm

The A-star algorithm is a highly effective path planning algorithm due to its simplicity, speed, and targeted heuristic search. It can efficiently narrow the search space and reduce problem complexity, achieving high path search efficiency. During robot path planning, the evaluation function is used to determine the nodes that need to be passed through at the next moment. Real-time evaluation of adjacent nodes is required, and In the A-star algorithm, the node with the smallest evaluation function value is chosen as the next position for the robot to move towards the target point, which allows the algorithm to continuously approach the optimal path. The evaluation function considers both actual cost and estimated cost, measured in Euclidean distance units, the evaluation function is as follows [19]:

$$f(n) = g(n) + h(n) \tag{11}$$

$$g(n) = D(n-1, n) = \sqrt{(x_n - x_{n-1})^2 + (y_n - y_{n-1})^2} \tag{12}$$

$$h(n) = D(n, p) = \sqrt{\left(x_p - x_n\right)^2 + \left(y_p - y_n\right)^2} \tag{13}$$

In the (11), f(n) is the evaluation function of node n in the workspace, which represents the total cost of the search and rescue robot at the node n in the path planning process.

In the (12), g(n) denotes the actual cost of the robot moving from the parent node of n to the node n in the workspace.

In the (13), the function h(n) denotes the approximate cost that the robot will incur while moving from the current node n to the destination node in the workspace. As it provides the heuristic information required for the search process, h(n) is a vital component in the evaluation function.

The success of the A-star algorithm is directly dependent on selecting an appropriate evaluation function, which is determined by the specific situation at hand. The key to selecting an appropriate evaluation function lies in choosing an appropriate heuristic function, as an inappropriate one will negatively impact the quality of the path planning. A heuristic function that more accurately estimates the actual cost will yield better results. The estimated value of h(n) restricts the evaluation function f(n) when the actual cost of moving from the parent node to the current node, g(n), is fixed. Therefore, nodes closer to the target point have smaller values of h(n), resulting in smaller values of f(n) and ensuring that the algorithm continuously moves towards the target point while searching for the shortest path.

4. Improved Artificial Potential Field

Since the environment is often unknown or partially known in practical applications, a single global path planning cannot cope with various situations. Using a single A* algorithm, path planning can be performed in a scene known to the environment. In the event of an unexpected change in the environmental scene while the robot is in motion, it may be unable to evade obstacles and arrive precisely at the target point, leading to a failed path planning. For example, some equipment distributed in the intelligent warehouse is known, and the cargo handling trolley can plan a path based on the known information to move the goods from the location to the destination. However, if some goods are temporarily stacked, the global path planning cannot be accurately carried out at this time, resulting in the cargo car unable to reach the target position. Therefore, a single A* algorithm cannot meet the actual needs of path planning [20]. Using only the APF method for path planning may result in low efficiency in generating paths as it is a local path planning algorithm, and lacks the ability to gain a global understanding of the environment. In addition, it has the defects of local minima and unreachable targets, so it will increase the amount of computation, fall into the dead cycle of path planning, and also lead to the failure of final path planning.

Based on the above research, both the single A* algorithm and the APF method have their limitations and are difficult to cope with special situations. Thus, to overcome the limitations of both global and local path planning methods, a hybrid approach is proposed in this study. The proposed method integrates the advantages of both methods, i.e., the ability to handle known environments and the ability to adapt to unknown environments, to achieve more efficient and effective path planning for mobile robots. In practical path planning, sensors are utilized to gather information and initialize the environment, establishing a comprehensive map. Building on this foundation, the enhanced A* algorithm is employed for global path planning, resulting in an optimal initial path. At the same time, the sensor is used to continue to obtain the surrounding environment, and the IAPF method is used for local path planning.

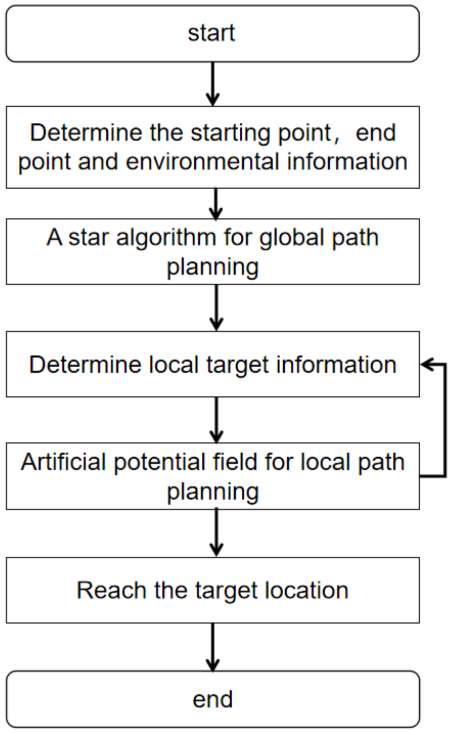

Figure 2. Mixed path planning flow chart.

Figure 2 provides a concrete form of the hybrid algorithm:

1. Using sensors for information collection and map construction: Using the sensors carried by the robot for environmental perception to convert environmental information into digital maps. Through map construction, static obstacles and dynamic obstacles around the robot can be identified and located.

2. Global path planning involves finding an optimal path using the improved A* algorithm after the map has been constructed. This technique is primarily used for long-distance movement, such as moving a robot from a starting point to a target point. To achieve efficient and safe path planning in the global stage, it is crucial to consider the robot's motion capabilities and environmental constraints.

3. Local path planning: In the process of robot travel, due to environmental dynamics and sensor errors and other reasons, there may be some local obstacles, then the robot needs to carry out local path planning. The APF method can be used for local path planning to generate a path to avoid obstacles. This path is usually used for detailed movement, such as the robot bypassing static obstacles or bypassing dynamic obstacles.

4. Real-time update path: In the process of robot travel, due to factors such as environmental changes and sensor errors, path planning needs to be updated in real time to ensure the safety and efficiency of robot motion. Therefore, in the process of robot movement, it is necessary to continuously obtain sensor data, update maps and path planning, and control the movement of the robot.

5. Experimental simulation

Using the planning method of the hybrid algorithm discussed in the previous section, we constructed a simulation environment in MATLAB. The environment is a 2D space of size 25*20, with 26 randomly placed red obstacles of radius 0.5. The robot is modeled as a circle with radius 0.2 and its starting and ending points are marked on the map. To showcase the efficacy of the hybrid algorithm, we conducted two sets of simulation experiments with different starting points, comparing the performance of the hybrid algorithm with that of the single artificial potential field algorithm.

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6. Experimental results

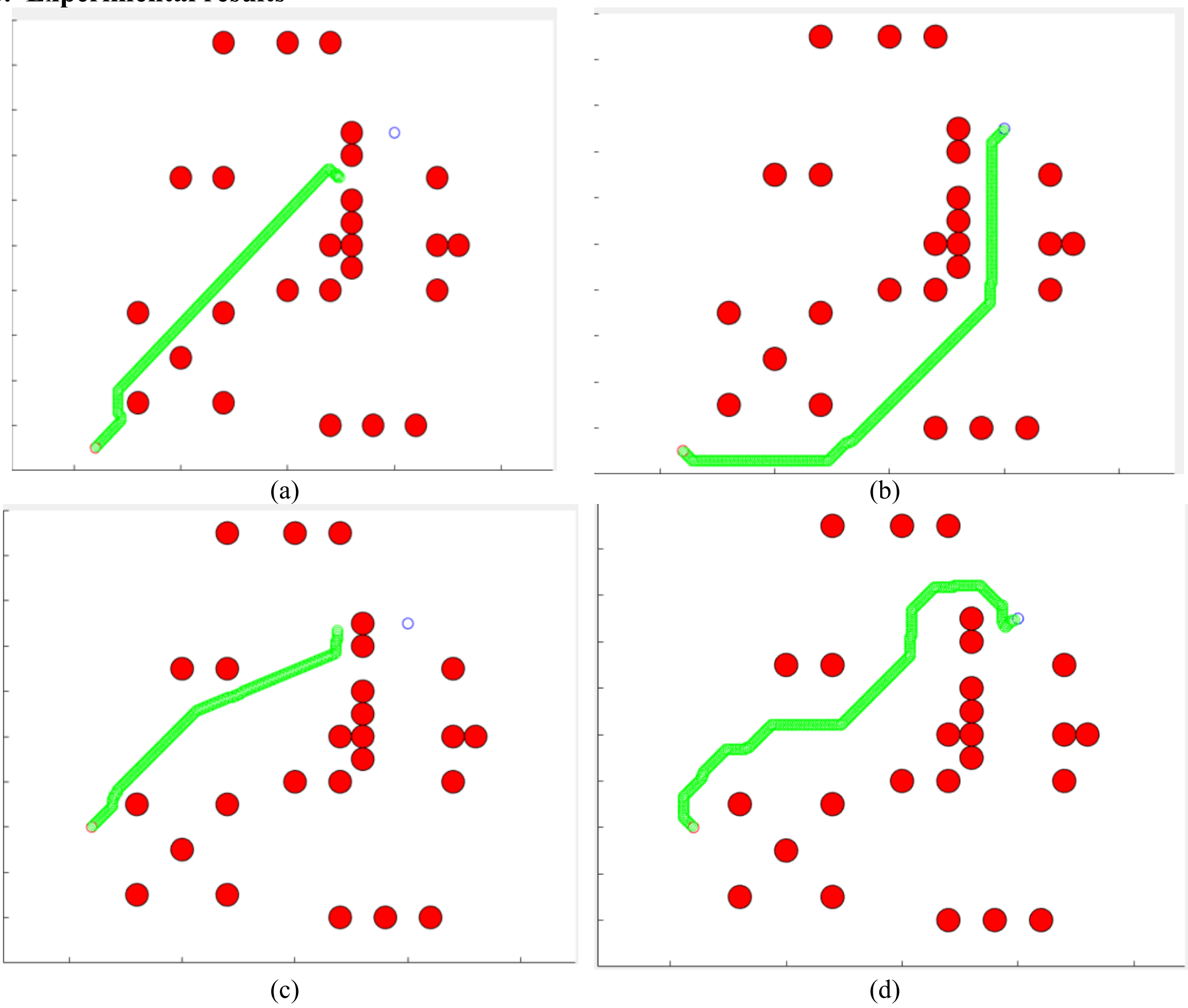

Figure 3. Comparison of simulation results for robot obstacle avoidance using APF and IAPF (a) Results of robot obstacle avoidance simulation with conventional APF algorithms; (b) Result of robot obstacle avoidance simulation with IAPF algorithms; (c)Results of robot obstacle avoidance simulation with conventional APF algorithms after changing the start point; (d)Results of robot obstacle avoidance simulation with conventional IAPF algorithms after changing the start point.

The experimental results on (a)(c) of Figure 3 show that the robots in the two groups of single artificial potential field algorithms have encountered local minima. In the optimized combination algorithm, (b)(d) of Figure 3, the robot does not fall into the local minimum point again, and changes some forward direction, and obtains a more reasonable path. Even though the starting point was changed, the robot was able to complete the path planning and obstacle avoidance.

The proposed hybrid path planning algorithm effectively addresses the issue of local algorithm oscillation around obstacles, which can prevent the robot from reaching the target point. By combining global and local path planning methods, the robot can have a comprehensive understanding of the environment and avoid falling into local minimum values, which is a limitation of using only local path planning. Additionally, the use of local path planning allows for a shorter planned path. The results of the simulations show that the proposed hybrid path planning algorithm is practical and effective.

7. Conclusion

The current study proposes an innovative technique for mobile robot obstacle avoidance utilizing APF. A-star is integrated into the development of the APF to enhance the ability to avoid local optima in the proposed approach. Additionally, the hybridization of the two algorithms results in better planning outcomes by complementing each other. The simulation results showcase the efficacy of the hybrid algorithm in mitigating the issue of the robot getting stuck in local minima. However, some limitations still exist in the traditional A* algorithm combined with the APF method. For instance, it is unable to detect local minima of random multiple individual obstacles, which calls for further optimization of the algorithm model. Furthermore, the investigation of dynamic and sudden obstacles will be a future research direction for this study.

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