Research on Path Planning Methods based on Mobile Robots

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Abstract. The path planning of mobile robots is a critical technique for achieving robot autonomy. With the rapid development of the robot industry, the demand for mobile robot path planning is expanding. The primary algorithms involved in mobile robot path planning are summarized, along with their characteristics, in order to enhance mobile robot path planning and achieve effective obstacle avoidance and dynamic path planning. The A* algorithm and the artificial potential field approach are examined first, along with a summary of their drawbacks and an analysis of their underlying theories. Second, a new algorithm that combines the artificial potential field approach and the A* algorithm is summarized. The potential field function of the APF method is used to drive the search for the A* algorithm, and the enhanced algorithm is compared and examined based on path length, obstacle avoidance effect, and iteration times. In order to achieve the combination of global and local planning abilities, this algorithm uses the enhanced A* algorithm for global path planning and enhances the APF algorithm for local dynamic planning on the determined path. A comparative analysis was conducted using the simulation image. It offers other researchers a more thorough and effective path planning method for mobile robots. Lastly, the drawbacks of the A*_APF fusion algorithm are highlighted, and recommendations for enhancement are made.

Keywords: Path planning, A* algorithm, Artificial potential field, Trajectory optimization, Algorithm fusion.

1. Introduction

Autonomous mobile robots have developed quickly as a result of COVID-19, and they are now widely employed in a variety of industries and fields, including agriculture, healthcare, mining, space missions, industry, military, and education.The demand for path planning for mobile robots is growing. In order to guarantee that mobile robots can autonomously plan paths and avoid obstacles in complicated situations, path planning is one of the key technologies to increase operating efficiency and stability. The primary issue is path planning in an uncharted territory.

Scholars at home and abroad have developed a variety of approaches for studying path planning, including the A* algorithm [1], the artificial potential field method [2], the rapid expansion random tree method [3], the particle swarm algorithm [4], and so on.Artificial potential field approach and A* algorithm are the most commonly employed among them. The Artificial Potential Field Method is a heuristic search algorithm that is popular for use in mobile robot path planning. It can achieve better results in the majority of mobile robot path planning problems, but there are some issues with local minima and unreachable targets. Therefore, Xu Xiaoqiang et al determined the estimated distance between obstacles. To help the robot avoid the trap area, the virtual target point is set ahead of time when it is due to fall into the local minimum within the projected distance [5]. Zhang Xu et al.proposed the fan-shaped area identification methodology, which is a great method to avoid dynamic obstacles [6]. Comparing the A* algorithm to other heuristic search algorithms like particle swarms and ant colonies, the A* method has a higher operating efficiency.Its implementation process is not very complicated. However, the path is not smooth and the usual A * algorithm has a lot of inflection points that make it easy to slant through the apex of barriers.In order to reduce the number and length of node searches, LIN et al incorporated parent node information to the A* beginning function and changed the weight [7]. To plan the energy-saving path, LIU et al developed the A* algorithm based on the distance-energy consumption search criterion; however, the path contains redundant turning sites and ignores the additional energy loss caused by frequent turns [8]. Improved A* algorithm, turning penalty value introduced to minimize number of turns, obstacle avoidance priority combined with waiting time devised, and automated guided vehicle (AGV) path planning realized by Li Teng et al. [9].

However, there are usually certain drawbacks to the conventional algorithm. To improve path planning, Yu Xiang et al coupled artificial potential field with A* algorithm to present APF-A* algorithm, which can perform efficient exploration in unknown static environment and effective and comprehensive map coverage [10, 11]. An algorithm that combines the artificial potential field approach (IA * -APF) and the A * algorithm was proposed by Hu et al. The improved artificial potential field technique uses the inflection point in the global path prepared by the improved A * algorithm as its subpoint [12].

Based on the path planning method of mobile robots, this paper introduces and analyzes the latest achievements of various improved new algorithms in obstacle avoidance and path planning under the condition of continuous improvement of the A* algorithm and artificial potential field method, and looks forward to the future development of path planning for mobile robots.

2. A* Algorithm

2.1. Traditional A* Algorithm

The most efficient direct search technique for determining the ideal path in a static environment is the A* algorithm, which combines heuristic search with the breadth-first approach. Based on the magnitude of the specified valuation function, it decides the best course of action. This is how the cost function is expressed:

$$\mathrm{f(n) = g(n) + h(n)} \tag{1}$$

The node n represents the current node, f(n) denotes the node's evaluation function, g(n) represents the real substitution value from the starting point to the node n, and h(n) represents the estimated substitution value from the node n to the destination point.The A* algorithm uses a cost function F (n) to find nodes in eight directions around it. It then expands from the starting point, uses the heuristic function H (n) to calculate the generation value of each node around it, chooses the next expansion point based on the lowest generation value, and repeats the process. Finally, find the path with the least cost from the target point back to the start node by searching along the parent node. This is the final path.The path cost is the smallest during the search process since every node on the path has the lowest cost [12].

When using the heuristic function of Euclidean distance, there is

$$h_\gamma(n) = \gamma \times \sqrt{((x_n - x_g)^2 + (y_n - y_g)^2)} \tag{2}$$

Here, γ represents the weighting coefficient, x_n, y_n denote the coordinates of the current key point, and x_g, y_g denote the coordinates of the destination point's key points.Through optimization, the shortest path between the current position and the desired position can be found [11].

In Figure 1, the conventional A* algorithm flow is displayed. The unselected node set in the A* algorithm is called open_set, and the chosen node set is called close_set.

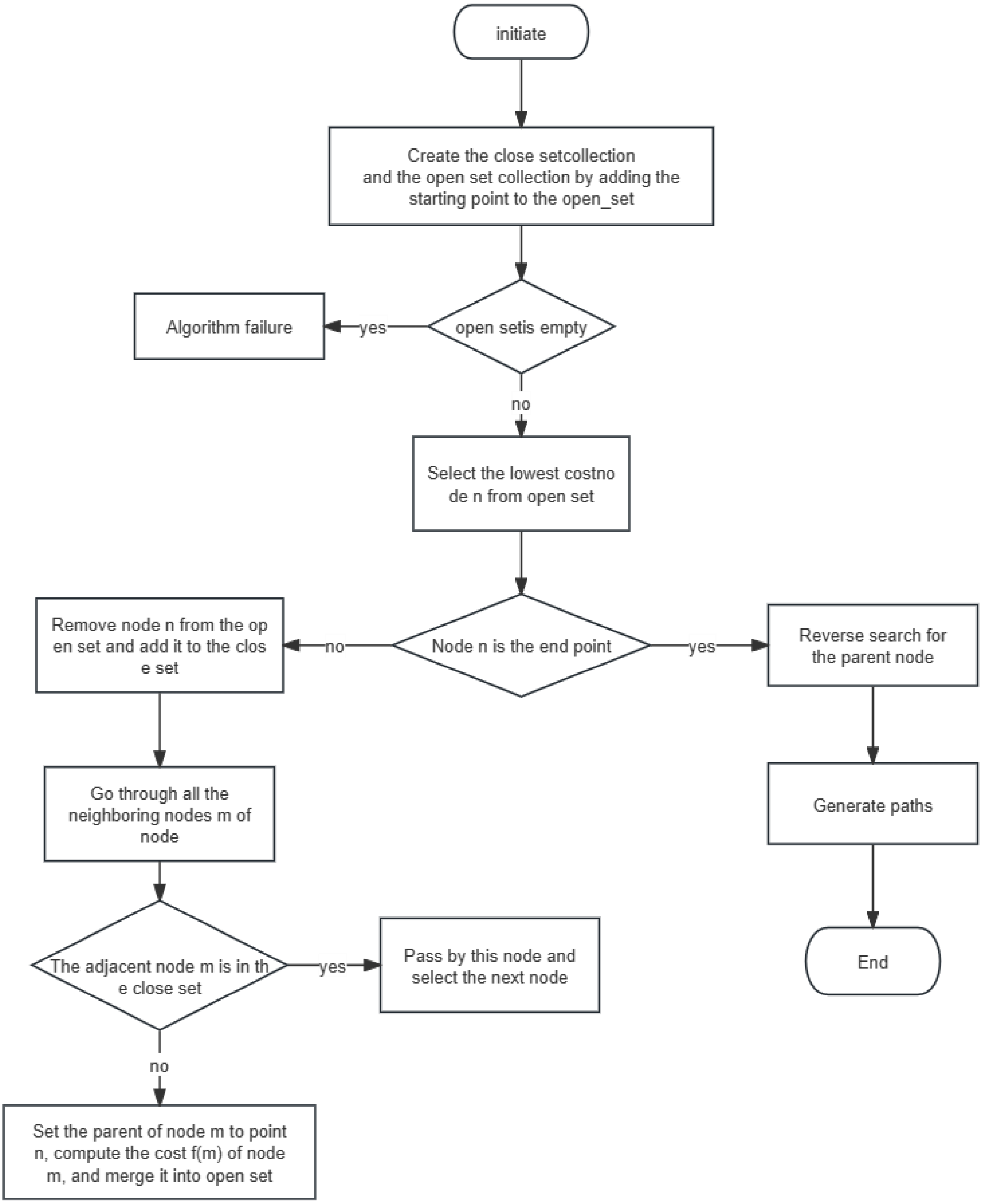


Fig. 1 Flow of original A* algorithm [11]

2.2. Environment Model Description

Path planning of the robot is highly dependent on its working environment; to effectively describe the environment of the robot, the controlled target is considered as a point-like object moving on a two-dimensional platform; therefore, the feasible area is represented by a white block on the raster map, and the moving trajectory of the target can be represented as a black block. The x coordinate represents the grid's horizontal axis, increasing in value from left to right; the y coordinate represents the grid's vertical axis, increasing in value from bottom to top; and the exact position of the grid is represented by $p(x_i, y_j)(i, j = 1,2,3, \dots, n)$.

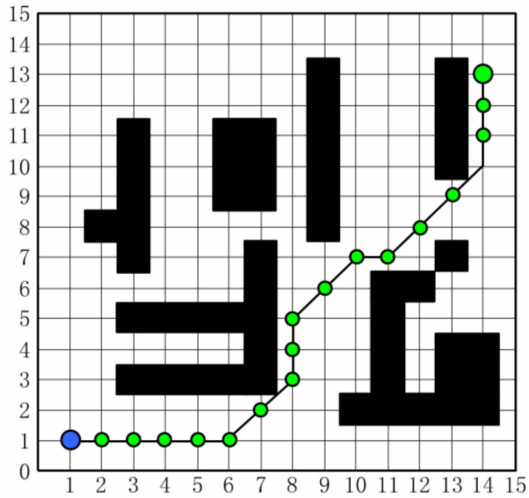


Fig. 2 Paths and nodes planned by traditional A* algorithm [13]

As seen in Figure 2, the classic A* algorithm has excessive turning angles, discontinuous path curvature, and numerous redundant nodes and sections. Despite its ability to carry out global path planning successfully, these factors contribute to the algorithm's low efficiency and poor safety in robot path planning.

3. Artificial Potential Field Method

3.1. Basic Principles of APF Algorithm

The fundamental idea behind the artificial potential field approach is to create a virtual potential field and use that potential energy field function to solve the obstacle avoidance problem. Virtual potential sources come in two varieties: repulsive force fields and gravitational fields. The objective is regarded by the potential energy field function as the gravitational pole and the obstacle the robot encounters as the repulsive force pole. The gravitational pole's gravity is described abstractly as the distance correlation function between the reference location (i.e., the mobile robot position) and the target position. The obstacle's distance correlation function with respect to the reference position is the repulsive force produced by the repulsive pole.As shown in Figure 3

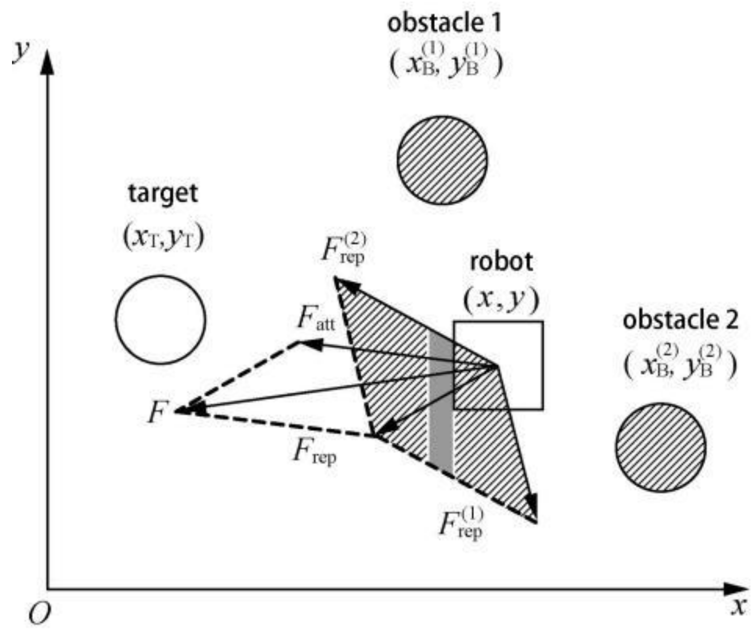


Fig. 3 Schematic diagram of artificial potential field method [14]

The gravitational potential field function U_{att} can be defined as:

$$U_{att}(q) = [m\rho^2(q, q_g) + k_{vl}\rho^2(V, V_g)]/2 \tag{3}$$

The corresponding gravitational force F_{att} can be expressed as

$$F_{att}(q) = m\rho(q, q_g) + k_{vl}\rho(V, V_g) \tag{4}$$

In the formula, m and k_{vl} are the normal quantities of gravitational field; $\rho(q, q_g)$ is the Euclidean distance between the robot and the target point; $\rho(V, V_g)$ is the relative velocity between the robot and the target point.

The repulsive potential field function U_{rep} can be defined as

$$U_{rep}(q) = \begin{cases} U_{repl} + U_{repv} & \rho(q, q_{obs}) \le \rho_0 \cap \alpha \in (-\pi/2, \pi/2) \\ U_{repl} & \rho(q, q_{obs}) \le \rho_0 \cap \alpha \notin (-\pi/2, \pi/2) \\ 0 & \rho(q, q_{obs}) > \rho_0 \end{cases} \tag{5}$$

(6)

$$U_{repv} = k_{v2}\rho^2(V, V_{obs})/2 \tag{7}$$

$$U_{repl} = \frac{k}{2}\left(\frac{1}{\rho(q, q_{obs})} - \frac{1}{\rho_0}\right)^2 \rho^2(q, q_g) \tag{8}$$

The corresponding repulsive force F_{rep} can be expressed as

$$F_{rep}(q) = \begin{cases} F_{repl} + F_{repv} & \rho(q, q_{obs}) \le \rho_0 \cap \alpha \in (-\pi/2, \pi/2) \\ F_{repl} & \rho(q, q_{obs}) \le \rho_0 \cap \alpha \notin (-\pi/2, \pi/2) \\ 0 & \rho(q, q_{obs}) > \rho_0 \end{cases} \tag{9}$$

$$F_{repv} = k_{v2}\rho(V, V_{obs}) \tag{10}$$

$$F_{repl} = k\left(\frac{1}{\rho(q, q_{obs})} - \frac{1}{\rho_0}\right)^2 \rho(q, q_g) - k\left(\frac{1}{\rho(q, q_{obs})} - \frac{1}{\rho_0}\right) \frac{\rho^2(q, q_g)}{\rho(q, q_{obs})^2} \tag{11}$$

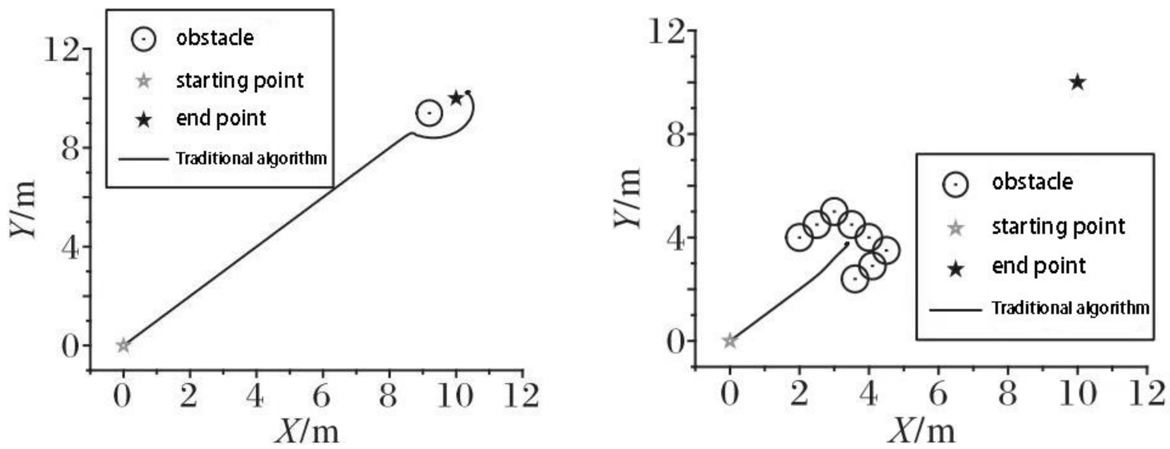
Among them, k and k_{v2} are the normal constants of the repulsion field; $\rho(q, q_{obs})$ represents the Euclidean distance between the robot and the obstacle; $\rho(V, V_{obs})$ represents the relative speed between the robot and the dynamic obstacle; ρ_0 is a constant, indicating the maximum range of the impact of obstacles on the robot; α is the relative movement direction of the obstacle and the angle between the line connecting the mobile robot and the obstacle. When $\alpha \in (-\pi/2, \pi/2)$, the obstacle The moving direction of the object is determined to be close to the mobile robot [15].

The conventional artificial potential field approach may swiftly design a collision-free course for an environment with only stationary obstacles by controlling the robot's movement through the magnitude and direction of the resultant force of gravity and repulsion force. Nevertheless, it frequently falls short of the planning specifications in the complicated dynamic obstacle environment, leading to issues like the inability to reach the goal position or an inadequately smooth final trajectory.

3.2. Defect Analysis of Artificial Potential Field Method

3.2.1 Target unreachable problem

The robot is unable to avoid an obstacle and reach the target point in the classic APF algorithm due to an excessive number of obstacles or a repulsive force between the obstacle and the target point. The primary cause is because the repulsion function's formulation ignores the distance between the target location and the mobile robot. The two scenarios are illustrated below for reference.



(a) There are obstacles near the target point (b) U-shaped obstacle

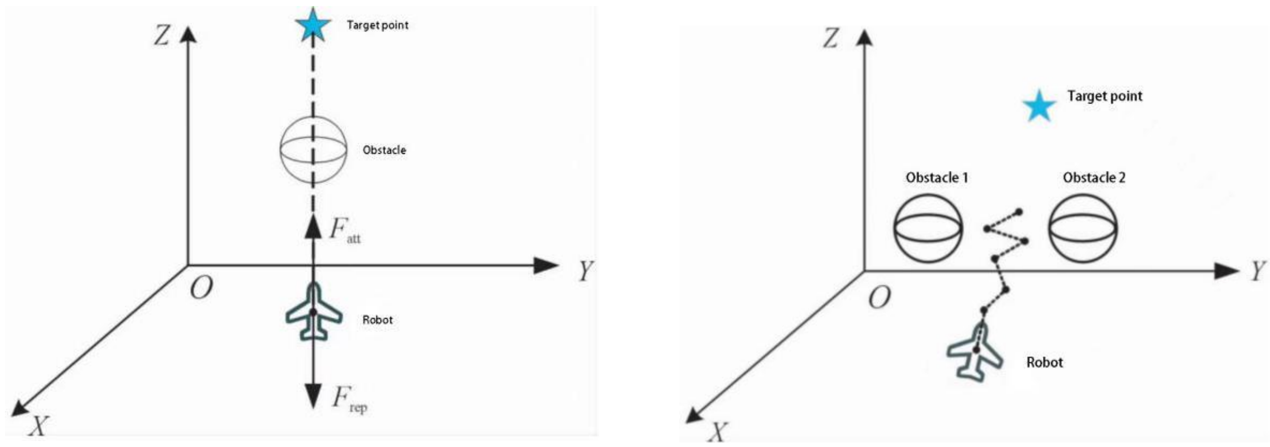
Fig. 4 Schematic diagram of unreachable target problem [5]

Because the objective location is so close to the obstruction, it attracts the robot less when there is an obstacle in the way. At this point, the obstacle's repulsive force outweighs the attraction of the target point, causing the robot to tremble near the target point and fail to reach it. As shown in Figure 4(a).

The robot is encircled by the barrier and unable to escape in a complicated obstacle environment, like a U-shaped obstruction, which results in the path planning function failing.As shown in Figure 4(b).

3.2.2 Stuck in local problems

Local minimum point and local oscillation problems make up the majority of the local difficulties in the conventional artificial potential field approach. In Figure 5(a), a typical local minimum problem is displayed. The robot, the target point, and the obstacle are all on the same straight line in Figure 5(a). The robot will remain stationary at a local minimum point that forms when the gravitational and repulsive forces are equal but opposite at that point on the straight line, and the resulting force is zero.Typical local oscillation phenomenon schematic diagram (Figure 5(b)). The robot experiences frequent and significant direction adjustments as it navigates across the small channel formed by two obstacles. It is likely that the robot will not be able to move along this course due to restricted maneuvering performance.



(a) Schematic diagram of local minimum problem (b) Schematic diagram of local oscillation phenomenon

Fig. 5 Schematic diagram of classic local problem [16]

4. Fusion of A* Algorithm and Artificial Potential Field Method(A*_APF)

4.1. A*_APF Research and Development Background

The A* algorithm works well for global planning, but it is not as effective for local planning in particular circumstances. For instance, it can be difficult to avoid obstacles and the calculating path may show broken lines in a barrier-filled environment. While the APF algorithm can accomplish some obstacle avoidance functions and is appropriate for local planning, there may be arrival and local issues along the way, and the planned path may not be the best option.To fulfill the path planning needs of mobile robots, many researchers combine the A* algorithm with the artificial potential field approach to obtain extensive coverage and efficient path planning in unfamiliar situations.

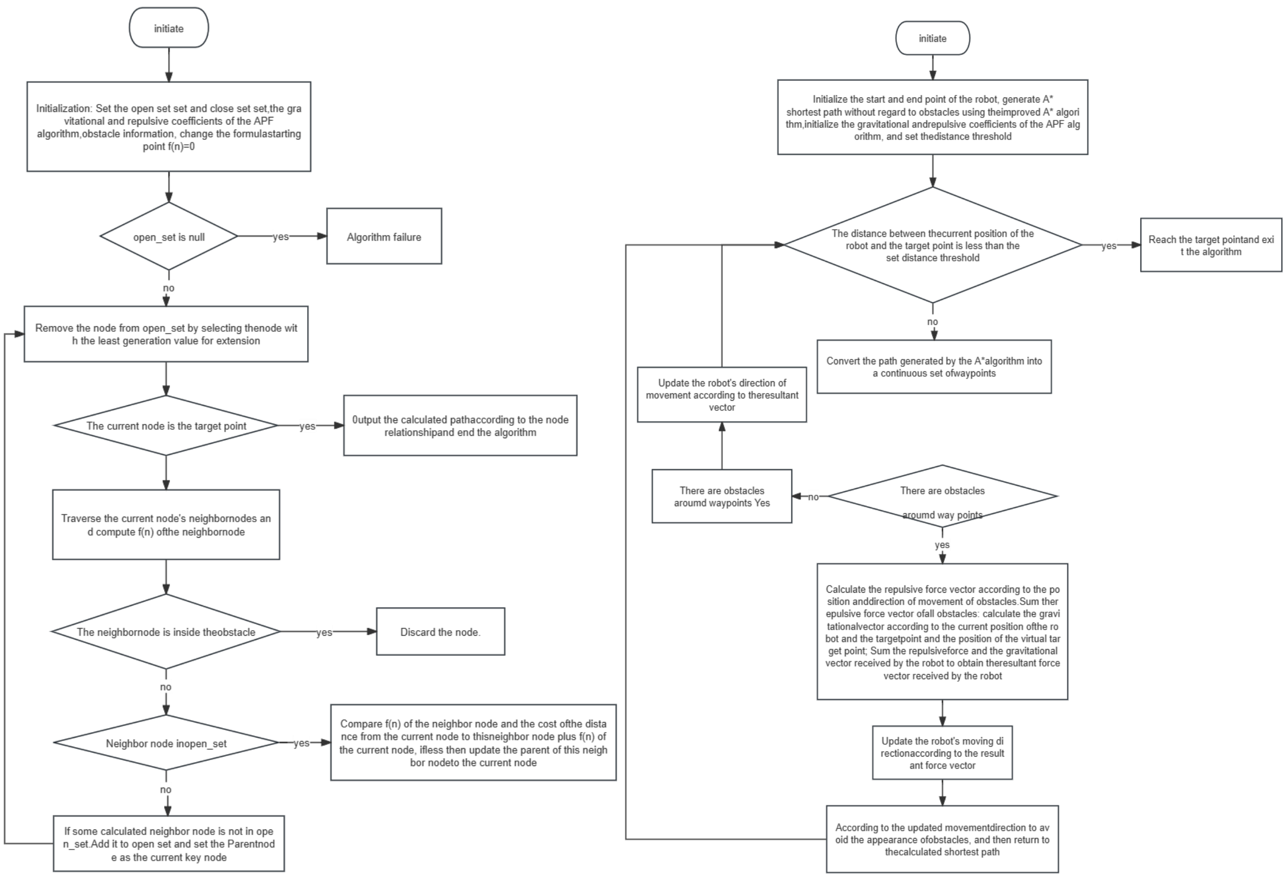
Yu Xiang and others used the APF algorithm to guide the search of the A* algorithm. Based on the improved A* algorithm, the improved cost value of each search key point not only includes the cost from the starting point to the key point and the total value of the improved heuristic function H_{new}, but also Plus the gravity and repulsion values calculated by the APF algorithm.Thus formula (1) is modified to:

$$\mathrm{f(n) = g(n) + H_{new}(n) + P(n)} \tag{12}$$

$$\mathrm{P(n) = k_{att} \times d(n,g) + sum(k_{rej}/d(n,b)^2)} \tag{13}$$

Where: P(n) is the potential energy at the key node n; $\mathrm{d(n,g)}$ is the Euclidean distance between the key node n and the target key point g. b is the position of the barrier; $\mathrm{d(n,b)}$ is the Euclidean distance between the key node n and the barrier b; $\mathrm{k_{att}}$ and $\mathrm{k_{rej}}$ are the coefficients of gravitational and repulsive forces [11].

The APF algorithm is used to improve f (n) of the A* algorithm again, comprehensively considering the distance to the target point and the distance to the unknown obstacle (which may be static or dynamic), making full use of the global search capability of the A* algorithm, and at the same time The APF algorithm can be used to avoid paths passing through obstacles, and can quickly adjust the direction when encountering obstacles to achieve dynamic obstacle avoidance. Figure 6 shows the path planning flow of the new algorithm implementation.



(a) Flow involving static obstacle avoidance (b) Flow involving dynamic obstacle avoidance

Fig. 6 Obstacle avoidance flow chart [11]

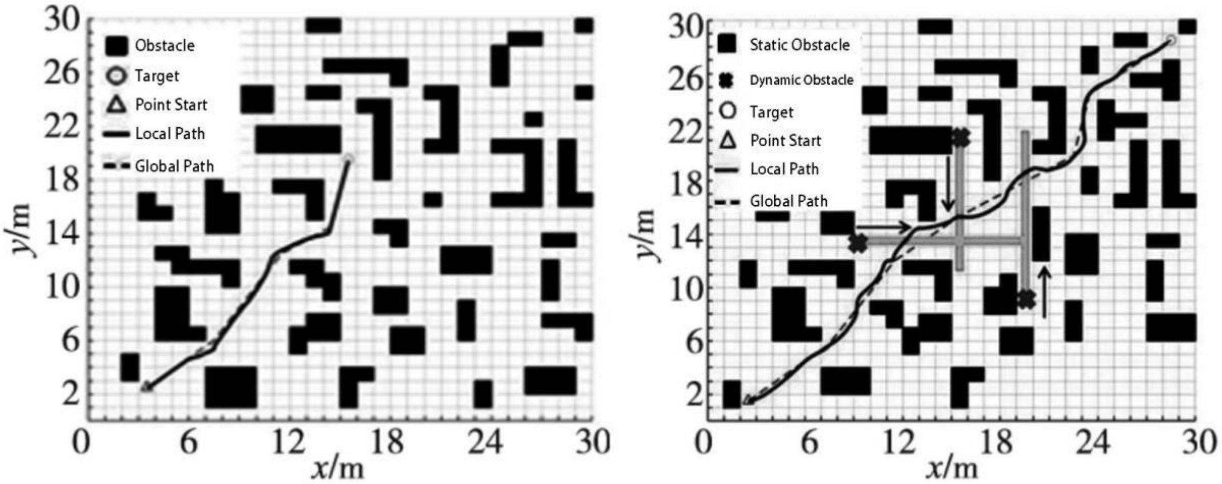
4.2. Simulation

To perform simulation study, Hu et al. built a dynamic obstacle environment and a trap area to confirm the novel algorithm's viability. The basic parameters of the simulation are shown in Table 1.

Table 1. Simulation parameter settings [12]

Parameter name	value
Gravitational gain coefficient m	15
Repulsive field constant k	50
Obstacle influence distance γ	2.5
Relative velocity repulsion constant σ	15
step size l	0.2

According to the parameters in Table 1, experiments were conducted in trap environment and dynamic environment respectively. Figure 7 shows the simulation results. In Figure 7(a), the inflection point of the global path in A*_APF serves as the virtual target point of the local path to help the robot escape from the trap area. In Figure 7(b), A*_APF can avoid dynamic obstacles well and maintain certain global optimality in unknown environment.



(a) Path map in trap area environment (b) Path diagram in dynamic environment

Fig. 7 Obstacle avoidance path results of fusion algorithm [12]

Table 2 displays the results of Yu Xiang and colleagues' Matlab-based obstacle avoidance simulation, which includes both static and dynamic obstacle avoidance simulations. The static obstacle avoidance simulation's initialization parameters are listed in Table 2. The initialization settings of the dynamic obstacle avoidance simulation are represented by 3 [11].

Table 2. Static obstacle avoidance simulation parameters

parameter	values
Repulsion correlation coefficient φ	0.8
Gravity proportional coefficient μ	1.5
Virtual point gravity coefficient φ	0.5
Obstacle collision range ρ	1.8
The ηth power of the robot and the target point	0.5
Simulation step size	0.1
The maximum number of iterations	500
Number of obstacles	34 or 8
Target point position	(23,24)

Table 3. Dynamic obstacle avoidance simulation parameters

parameter	values
Repulsion correlation coefficient φ	0.75
Gravity proportional coefficient μ	1.5
Virtual point gravity coefficient φ	0.5
Obstacle collision range ρ	2
The ηth power of the robot and the target point	0.5
Simulation step size	0.1
Number of dynamic obstacles	7
Number of static obstacles	17
Target point position	(10,10)

As shown in Figure 8, it is better to use the optimal node generated by the improved A* algorithm as the virtual target key point to solve the local problem, while ensuring the shortest and smooth path length.

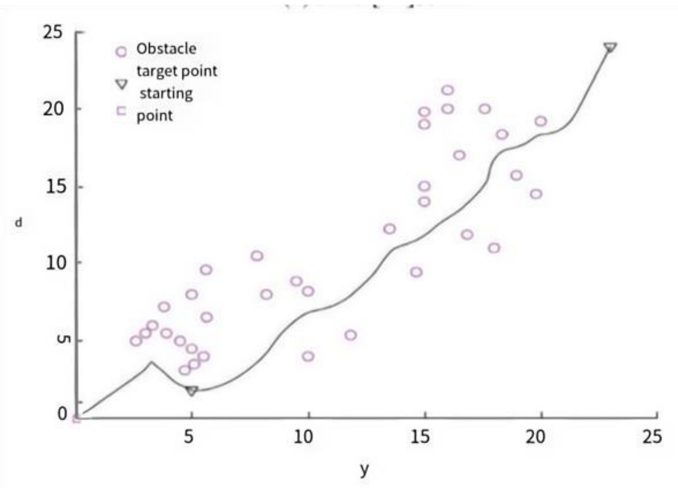


Fig. 8 Simulation results of improved algorithm [11]

As shown in Figure 9. In the figure, static obstacles are purple squares, dynamic obstacles are black squares, mobile robots are red triangles, and green hexagons are target points. The motion direction of dynamic obstacles is different. Through observation, it can be seen that fusion algorithm A*_APF can achieve the effect of dynamic obstacle avoidance, and ensure smooth and optimal path while avoiding obstacles, without polygonal path.

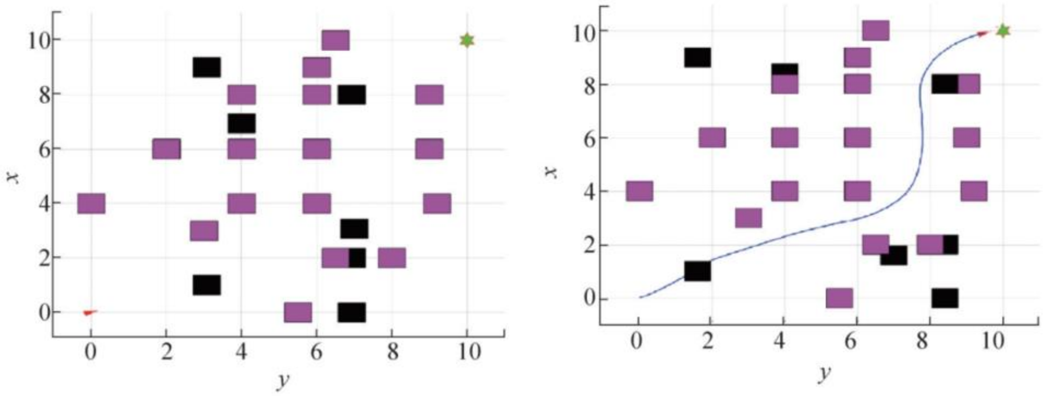
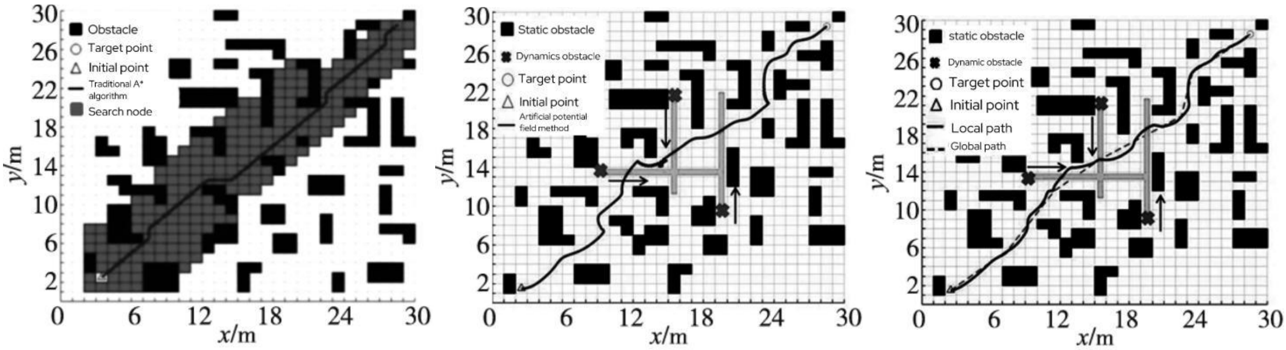


Fig. 9 Simulation results of dynamic obstacle avoidance [11]

5. Discussion

5.1. Comparison and Analysis of Simulation Results

The next graphic displays the simulation results of A* algorithm, the artificial potential field method, and A*_APF algorithm so that users may see how traditional methods fusion algorithms differ from one another visually.



(a) A* algorithm (b) APF algorithm (c) A*_APF algorithm

Fig. 10 Simulation results comparison [12]

It is easy to see the benefits and drawbacks of each when compared to Figure 10. Because the A* algorithm allows the robot to move to a maximum of 8 surrounding grids, the path suggested by the algorithm in the raster map environment is not optimal. The robot path planning system has several drawbacks that contribute to its low efficiency, including a slow search speed, redundant nodes, and a large number of inflection points. However, A * method is crucial to global path planning because it may search the ideal path based on the evaluation function after traversing all available nodes.

The artificial potential field method, a heuristic search algorithm, is frequently used for mobile robot path planning because of its simple algorithm and strong real-time performance. It can successfully solve the majority of mobile robot path planning problems, but there are some issues with local minimum and unreachable target. As a result, the classic artificial potential field approach is typically used in environments containing only static impediments. It frequently fails to meet the planning needs in the complicated dynamic obstacle environment.

Recently, researchers both domestically and internationally are still working to refine the two algorithms, with the goal of giving the A * algorithm global optimization and the artificial potential field approach real-time obstacle avoidance. The two algorithms are combined in the A*_APF algorithm to overcome their own flaws and improve the outcome of the estimated path. In A*_APF, the A* algorithm performs global path planning in a known obstacle environment, and the inflection point of the global path is sequentially employed as the virtual goal point of the artificial potential field method path planning until the algorithm is finished.

5.2. Future Outlook and Suggestions

Even while the A*_APF algorithm as it is now can handle the path planning challenge for two-dimensional mobile robots, there are still certain areas that might use further development, such as:

(1) Environmental modeling. The extant literature on path planning primarily treats the robot as a particle and abstracts the task space into an idealized, easily solved model, ignoring the robot's size and the complexity of the real environment. This results in a poor performance of the robot during path planning. Future developments should consider the robot's unique model and attributes to improve the realism of the simulation effect.

(2) Collaborative path planning for multiple robots. The majority of research conducted now focuses on one robot's path planning. Some unique working settings require many robots to collaborate, with greater criteria for cooperation and more limits than a single robot might have. In the future, the effectiveness of multi-robot overall and local relationships' path planning can be enhanced by combining classical and swarm intelligence algorithms.

6. Conclusion

The differences between the classic artificial potential field approach and the traditional A* algorithm are contrasted with the simulation path planning results, and their benefits and drawbacks are examined. The current most used method for mobile robot path planning is A*_APF, which combines the benefits of the A* and APF algorithms. The current algorithmic accomplishments are reviewed in this work, along with a detailed analysis of the fusion algorithm's path for improvement, corroborated by flow charts and simulation images. Lastly, with the rapid development of science and technology, environmental modeling and multi-robot collaborative path planning are increasingly becoming research hotspots. However, despite some significant progress, there are still many research gaps and future development directions in these two fields, which need to be explored and breakthrough. In short, environmental modeling and multi-robot collaborative path planning, as two important research fields, have broad application prospects and far-reaching research significance. Through in-depth discussion of the gaps and future development directions, we are expected to inject new vitality into the development of these two fields and promote scientific and technological progress and social development.

References

[1] Lai Xin, Li Jiahe, Chambers J. Enhanced Center Constraint Weighted A* Algorithm for Path Planning of Petrochemical Inspection Robot[J]. Journal of Intelligent & Robotic Systems, 2021, 102(4): 78.

[2] Orozco-Rosas U, Montiel O, Roberto Sepúlveda. Mobile Robot Path Planning Using Membrane Evolutionary Artificial Potential Field[J]. Applied Soft Computing, 2019, 77: 236-251.

[3] hen Zhimei, Li Min, Shao Xuejuan, et al. Obstacle avoidance path planning of bridge crane based on improved RRT algorithm[J]. Journal of System Simulation, 2021, 33(8): 1832-1838.

[4] Ajeil H F, Ibraheem I K, Sahib M A, et al. Multi objective Path Planning of an Autonomous Mobile Robot Using Hybrid PSO-MFB Optimization Algorithm[J]. Applied Soft Computing, 2020, 89: 106076.

[5] Xu Xiaoqiang, Wang Mingyong, Mao Yan. Mobile robot path planning based on improved artificial potential field method[J].computer application,2020,40(12):3508 - 3512.

[6] Zhang Xu, Cheng Chuanqi, Hao Xiangyang, et al. A robot dynamic path planning algorithm that takes into account global and local characteristics [J].Journal of Surveying and Mapping Science and Technology,2018, 35(3):315 - 320.

[7] Lin M X, Yuan, Z, et al. Path planning of mobile robot based on improved A* algorithm[C]//Proceedings of the 29th Chinese Control and Decision Conference. Washington, D.C.,USA:IEEE,IEEE,2017:3570-3576.

[8] Liu S, Sun D. Minimizing energy consumption of wheeled mobile robots via optimal motion planning[J].IEEE/ASME Transactions on Mechatronics,2013,19(2):401-411.

[9] Li T, Ding P, Liu J. Multi-stage Multi AGV Path Planning With Walk Under Shelves for Robotic Mobile Fulfillment Systems[J]. Journal of System Simulation, 2022, 34(7): 1512-1523.

[10] Liu X. et al. Ergodic path planning algorithm based on improved A* algorithm in unknown environment.Ordnance Industry Automation, 2024, 1(43) : 01.

[11] Yu X, Jiang C, Duan S, et al. Path Planning for Improvement of A* Algorithm and Artificial Potential Field Method[J]. Journal of System Simulation, 2024, 36(3): 782-794.

[12] Hu Z, Xu B. Dynamic path planning integrating A* algorithm and artificial potential field method. Combined Machine Tools and Automated Processing Technology, 2023, 7: 46-49.

[13] Chen J, Xu L, Chen J, Liu Q. Mobile robot path planning using improved A* and dynamic window methods [J]. Computer Integrated Manufacturing Systems, 2022, 28(6): 1650-1658.

[14] Shi Z, Mei S, Shao Y, et al. Research status and prospect of path planning for mobile robots based on artificial potential field method [J]. Journal of Chinese Agricultural Mechanization, 2021, 42(12):182-188.

[15] Wang H, Hao C, Zhang P, Zhang M, Yin P, and Zhang Y. Mobile robot path planning based on A* algorithm and artificial potential field method. Chinese Mechanical Engineering, 2019, 30(20):2489.

[16] Wu Qian, Zeng Q, Luo J, et al. Application research on improved artificial potential field method in UAV path planning[J].Journal of Chongqing University of Technology(Natural Science), 2022, 36(3): 144-151.