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REVIEW ARTICLE

# A Review of Research on Shortest Path Planning Algorithms for Mobile Robots

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**Abstract:** ***Background*:** Path planning technology has a wide range of applications in many fields. Applications in the field of high technology include: autonomous and touchless action of robots; obstacle avoidance and defense flight of drones; cruise missiles to avoid radar search, anti-bouncing attacks, and to complete the task of sudden defense and demolition. Applications in daily life include: GPS navigation; road planning based on GIS system; urban road network planning and navigation. Applications in the field of decision-making management include: vehicle problem (VRP) in logistics management and similar resource allocation problems in resource management. Routing problems in the field of communication technology. Any planning problem that can be topologized as a point and line network can basically be solved by the method of path planning. Different intelligent algorithms have different characteristics, and their application scope and fields are also different, so it is of great significance for the development of path planning technology to study the path planning intelligent algorithms from the characteristics of the algorithms themselves and their applications.

***Objective*:** Analyze the advantages and disadvantages of various types of planning algorithms, look forward to the future development trend of mobile robot path planning, and provide certain ideas for the research of mobile robot path planning.

***Method*:** Search journals, patents, conferences, and papers related to mobile robot path planning, and summarize and analyze the advantages and disadvantages of various planning algorithms.

***Results*:** Based on the research results of many scholars, this study summarizes different mobile robot path planning methods. It is divided into four categories: traditional planning, intelligent search, artificial intelligence and local obstacle avoidance. This paper introduces and analyzes the latest research results of these types, including their design ideas, advantages and disadvantages, and improvement measures. The research methods adopted are analyzed in order to maximize the advantages of each algorithm and expand the application field of robot path planning to provide ideas and references.

***Conclusion*:** This paper provides guidance for the design and optimization of robot path planning. Finally, this paper summarizes the future development trend of robot path planning, and looks forward to the future development trend and key areas of robot path planning.

**Keywords:** Path planning, mobile robots, algorithm classification and summarization, global planning, local planning.

## 1. INTRODUCTION

Mobile Robot Path Planning Technology is the process by which a robot autonomously plans a safe path of operation to efficiently complete a task, using sensors to sense the environment [1].

It addresses three main problems: 1) enabling the robot to move from an initial point to a target point; 2) using algorithms to enable the robot to bypass obstacles; and 3) optimizing the robot's trajectory as much as possible while completing the task. This technology is one of the core elements of intelligent mobile robot research, originating in the 1970s and accumulating a large number of research results.

Based on the existing research results of mobile robot path planning algorithm, this paper divides the existing algo-

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rithms into four categories: traditional planning algorithm, intelligent search algorithm, artificial intelligence algorithm and local obstacle avoidance algorithm [2, 3]. The mainstream algorithm of mobile robot path planning is shown in Fig. (**1**).

## 2. CONVENTIONAL PLANNING ALGORITHM

Conventional planning algorithms usually need to establish a geometric model of obstacles in a known environment and select an appropriate path for geometric model path planning. This kind of algorithm depends on the display expression of the environment.

### 2.1. Bug Algorithm

When the mobile robot only has limited computing power, the simple structure of the Bug algorithm is the most simple and effective path planning algorithm. In the Bug1 algorithm proposed by Lumelsky, the robot will plan by bypassing the edge of the obstacle [4]. This method is inefficient, but it can ensure that the robot will reach any reachable goal. Aiming at the problem of low efficiency of Bug1 algorithm, Lumelsky proposed Bug2 algorithm based on Bug1 algorithm [5]. Bug2 is more ' greedy ' than Bug1, which effectively shortens the planning path, but the disadvantage is that in the case of complex environment, Bug2 algorithm may judge that the target point is not reachable.

Aiming at the problem that the standard Bug algorithm always bypasses in the same direction when encountering obstacles and has low efficiency, Kamon proposed the DistBug algorithm and the Tangent Bug algorithm [6, 7]. Both algorithms overcome the defect that the standard Bug algorithm may fall into a cycle around the circular obstacle, but they cannot guarantee the global optimization of the path and real-time fast online planning. Aiming at the problem that the robot in the Bug algorithm does not make full use of the adjacent environment information in the limited area that can be detected at any time in the planning process, Kang Liang proposed to use the concept of virtual obstacle to deal with the defect that the mobile robot is easy to wander around the local extremum point on the basis of the original Bug algorithm, which improves the optimization of the path and the completeness of the algorithm. However, this algorithm does not consider the existence of dynamic obstacles in the environment [8]. Peng *et al.* proposed the Multi-Bug algorithm, which adds the crawler splitting rule and the crawler death condition judgment rule [9]. Experiments show that the algorithm is better than the DistBug algorithm in reducing the path cost, real-time performance, and versatility.

### 2.2. Grid Map

Grid map (GM) is generally used as an environmental modeling technique for path planning. As a method of path planning, it is difficult to solve the problem of complex environmental information.

The idea is to discretize the external environment into grids of the same size according to a specific resolution. Each grid has only two states. The path planning algorithm occupies a grid and plans a path composed of multiple grids by searching for free grids and avoiding obstacles. This method is simple and easy to implement, and it also has the ability to express irregular obstacles. The disadvantage is that the representation efficiency is not high, and there is a contradiction between space-time overhead and solution accuracy. The diagram of the principle is shown in Fig. (**2**).

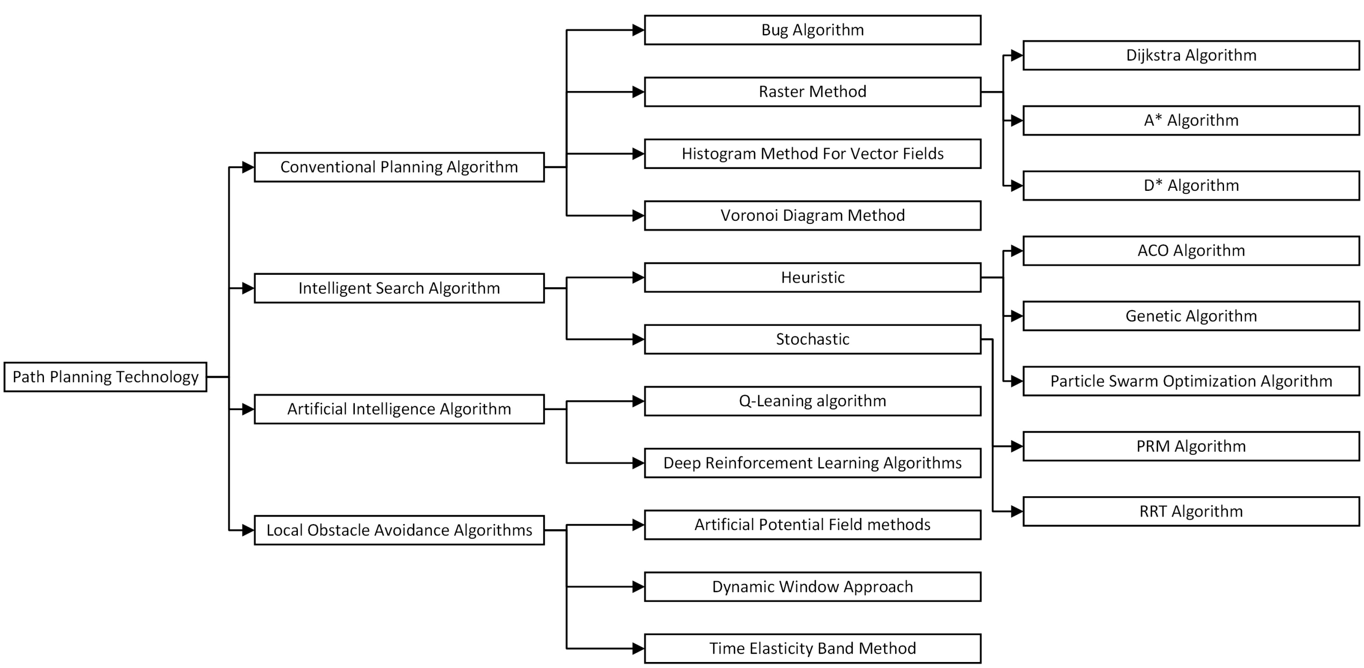


**Fig. (1).** Classification of path planning algorithms for mobile robots.

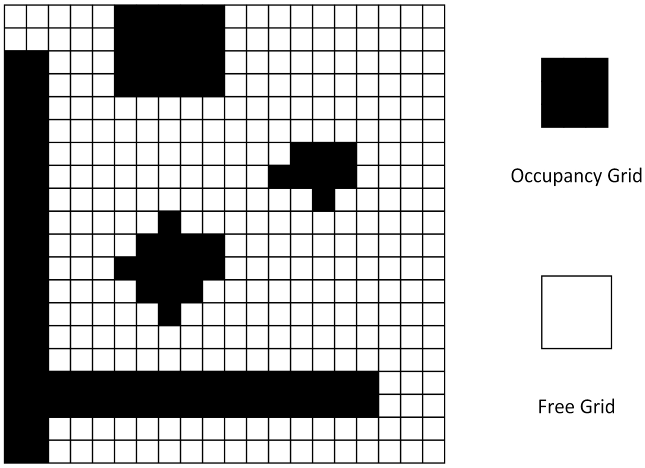


**Fig. (2).** Schematic diagram of the grid map method. *(A higher resolution / colour version of this figure is available in the electronic copy of the article).*

### *2.2.1. Dijkstra Algorithm*

Dijkstra algorithm belongs to the breadth-first algorithm, which is to obtain the shortest path through the forward traversal comparison of all nodes [10]. Because it will traverse all nodes, the success rate of the shortest path is high and the robustness is good. However, this algorithm belongs to the undirected search algorithm, and many traversal nodes and low efficiency are the fatal shortcomings when it is applied to large-scale complex path topology networks [11]. In addition, the Dijkstra algorithm cannot deal with the problem of negative weight edges

At present, the research and improvement of Dijkstra algorithm focus on algorithm optimization and algorithm application. For example, Idwan studied the heuristic algorithm to improve it and applied it to find the shortest path in large-scale graphics [12]. The experimental results show that the improved algorithm has obvious advantages in terms of input / output operation time and quantity. Tintor studied the use of distributed sparse matrix to optimize it and applied it in translucent optical network routing, which proved the effectiveness of the improved algorithm in opaque networks [13].

Zhou Lei *et al.* optimized the Dijkstra algorithm with the data structure of adjacent linked list and minimum binary heap [14]. The improved algorithm has reduced running time and improved efficiency. In order to solve the problem of path planning efficiency of AGV in factory logistics transportation, Tang Hongjie proposed a Dijkstra algorithm with storage mode change, and stored the storage model of unextended nodes through binary heap [15]. The algorithm has effectively improved the operation efficiency and occupied memory space. Khadr Mohamed S studied the control and path planning of tracked mobile robot based on Dijkstra algorithm in ROS [16]. The results show that the method can successfully realize the obstacle avoidance path planning.

### *2.2.2. A* Algorithm*

The A* algorithm is based on the Dijkstra algorithm, and the heuristic function is designed according to the prior information of the starting point and the ending point, so as to reduce the number of search expansion nodes and improve the efficiency of path search [17]. The core idea of the algorithm is to select the block with the lowest ' cost ' by comprehensively considering the actual distance and heuristic distance, so as to achieve the goal of searching the shortest path as efficiently as possible.

The advantages of A* algorithm are less extended nodes, good robustness, fast calculation speed and fast response to environmental information. The disadvantage is that the planning path often has more inflection points and insufficient global optimization ability.

Researchers have also given different solutions to various defects of the A* algorithm. Aiming at the problem of unsmooth path, Min Haitao added the cost of path curvature in the design of heuristic function, which improved the smoothness of the path [18]. Other studies are to optimize the generated path and increase the smoothness of the path. For example, Chen Jiao *et al.* combined the Floyd algorithm to optimize the path, and Chen Jiabao smoothed the path through the B-spline curve, which effectively improved the smoothness of the path, and the required performance did not increase significantly [19, 20]. Aiming at the problem that the traditional A* algorithm has insufficient global optimization ability, Zhang Xinyan *et al.* proposed an improved A* algorithm with time factor to find a path scheme with fewer turns [21]. The results show that the improved algorithm has advantages in path length and planning time.

In order to solve the problems of large memory overhead and long calculation time of A* pathfinding algorithm in large scenarios, Zhao *et al.* proposed an improved A* algorithm based on jump point search algorithm to replace a large number of unnecessary nodes that may be added with jump points, thus reducing the amount of calculation [22]. The improved A* algorithm can effectively improve the pathfinding speed. Ou *et al.* tried to use bidirectional A* search, and the results showed that the search efficiency was improved by about 40% [23]. Zhao *et al.* adopted a variable-scale A* programming algorithm to improve the computational efficiency while maintaining a high resolution [24].

In view of the situation that path planning is prone to conflict and locking in multi-robot environment, Liao *et al.* increased the actual cost of path turning cost and path overlap on the basis of A* algorithm, which effectively reduced the occurrence of this situation [25].

### *2.2.3. D* Algorithm*

The D* algorithm is developed from the A* algorithm, and its principle innovation is reflected in the dynamic updating of the heuristic estimates of the nodes with the passing of the search process, taking into account changes and updates from previous searches in order to progressively obtain better path planning results [26].

It is suitable for scenarios where the environment is unknown or the environment is dynamically changing, especially in the case of incremental update, it also has high search efficiency and path planning speed. However, the D* algorithm does not improve the shortcomings of the tortuous path in the A* algorithm. It also requires more computing resources and has a higher dependence on heuristic functions than the A* algorithm. The heuristic function of the algorithm is shown in Fig. (**3**).

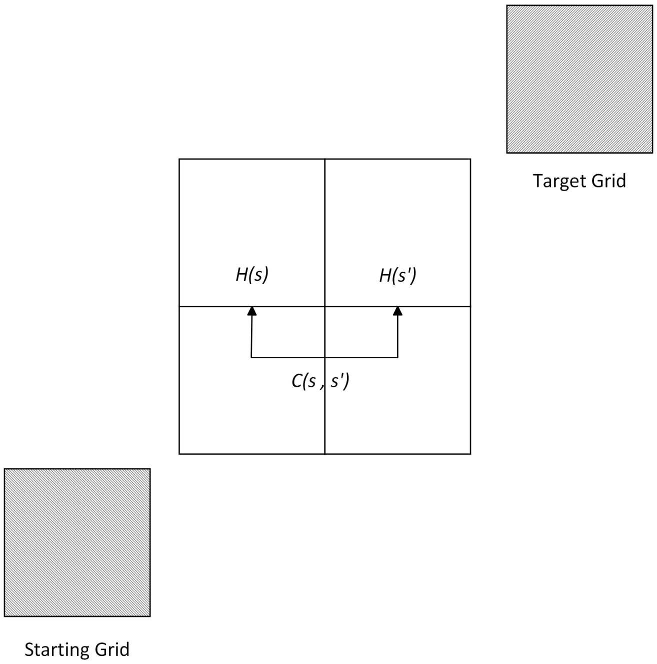


**Fig. (3).** Schematic diagram of the heuristic function. *(A higher resolution / colour version of this figure is available in the electronic copy of the article)*.

Similar to A* algorithm, the improvement of D* algorithm is mainly focused on two aspects: improving path smoothness and improving search efficiency. Zhu *et al.* used the uniform B-spline curve fitting model for path smoothing [27]; Liu *et al.* coordinated the relationship between path length and smoothness by adding a' turning factor ' to the path smoothness function [28]. Both methods considered smoothing in path generation, reflecting the different focus from smoothing the generated path again. In order to improve the search efficiency, Zhang *et al.* used the jump point search algorithm to reduce the search time in the D* algorithm to improve the A* algorithm, so as to speed up the search process. Another idea is to narrow the search area to improve efficiency [29]. For example, Wang introduced Voronoi diagram to obtain local optimal target points and improve the computing power of the algorithm [30]. This idea needs to be used with other improved methods, otherwise it is easy to fall into the local optimal solution problem.

In practical application, Wang Xiaokang provides a path planning method for flight area using D* algorithm, which solves the technical problem of low planning efficiency in the existing methods to a certain extent [31]. A path planning method based on D * lite algorithm and multiple intermediate voxels is proposed for multi-objective three-dimensional dynamic path planning [32].

### 2.3. Vector Field Histogram Method

Vector field histogram method (VFH) was proposed in 1991 [33]. The core idea of this method is to express the environmental information as vector field and histogram, and to plan the moving path of the robot by analyzing the histogram to select the safe direction. The algorithm flow is shown in Fig. (**4**).

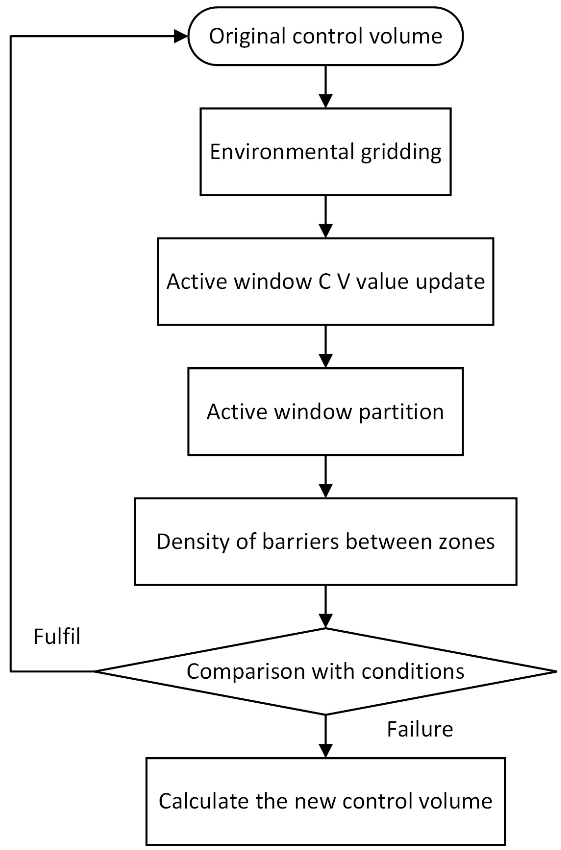


**Fig. (4).** Flow of VFH algorithm.

The advantage of the VFH method is that it does not require global map construction and positioning, and only relies on local laser scanning data. It has the characteristics of strong real-time performance, high computational efficiency and good adaptability, which enables mobile robots to quickly and reliably perform obstacle avoidance and path planning in complex environments. However, because the VFH method only considers the local laser scanning data, it is easy to cause the algorithm to fall into the local minimum value in the narrow area, and the range and resolution of the laser scanning may be limited, resulting in the inaccuracy of the path planning.

At present, the application of VFH algorithm in practice has the following directions [34]: 1) set more uniformly distributed high-resolution sensors. 2) Using mathematical methods and simulation experiments to determine the appropriate decision threshold. 3) Gridding and data processing of the environment. These three methods have a certain degree of improvement in the application of the decision-making efficiency improvement algorithm. For the improvement of VFH algorithm itself, there are VFH+ algorithm and VFH* algorithm proposed by Ulrich [35, 36].Compared with the traditional VFH algorithm, VFH+ algorithm takes more information into account when constructing histogram, such as the distribution and shape of obstacles, the shape of the robot, *etc.,* which can more accurately represent the feasible motion direction in the environment and improve the versatility of the algorithm. The VFH* algorithm is more inclined to improve the computational efficiency and optimize the dynamic environment.

Zhu Shaoming applied a dynamic window that can automatically adjust the range, and set adaptive thresholds under different window modes, so that the robot can quickly adapt to different environments while reaching the target point without collision and smoothly [37].

### 2.4. Voronoi Diagram Method

The Voronoi diagram method is an algorithm that combines the Voronoi diagram characteristics with the path planning algorithm. The core idea is that the method divides the target area into several sub-regions, uses the equidistant points of adjacent two points on the obstacle boundary to construct all the boundary lines, and then uses the search algorithm to obtain the collision-free path [38]. The Voronoi diagram method enables path planning to better consider the geometry and connectivity of the environment, and is more suitable for complex environments. However, the cost is high computational complexity and may be limited by the local optimal solution problem, and it cannot adapt to changes in a dynamic environment in time. Additional mechanisms are needed to deal with dynamic obstacles.

Aiming at the path planning problem of mobile robots using Voronoi diagram method in complex dynamic environments, Ayawli *et al.* proposed an improved algorithm that adds nodes to the initial route map nodes to calculate a new path for re-planning and discards failed nodes [39]. The algorithm can effectively determine the collision threat moving obstacles and avoid unnecessary re-planning calculations. Aiming at the problem of multiple mobile robots in dynamic unknown environment, Hu *et al.* proposed a multi-mobile robot cooperative exploration strategy based on Voronoi partition and a collision-free algorithm based on deep reinforcement learning [40]. Compared with the traditional method, this strategy reduces the overall time and energy consumption of task completion, and verifies the effectiveness of the collision-free algorithm. Zhu proposed a multi-UAV cooperative region algorithm based on Voronoi diagram centroid, and proposed a DCPS strategy for dynamic environment changes [41]. The strategy uses the V-graph centroid to guide the UAV to move toward the target point, thereby improving the search efficiency and improving the computational efficiency of the algorithm.

Jiang Lin provides a Voronoi path planning algorithm for new skeleton extraction of mobile robots, which removes the sharp points on the path and makes the final optimized path smoother [42].

## 3. INTELLIGENT SEARCH ALGORITHM

The intelligent search algorithm is an algorithm that approaches the optimal solution through randomly generated initial solutions or sampling points and multiple iterations. Its biggest feature is that it can continuously obtain new information in the planning to optimize the path, which is random, so its solution is not unique.

### 3.1. Heuristic

The heuristic intelligent search method is proposed relative to the traditional deterministic search algorithm. The algorithm randomly generates a feasible initial solution and uses an iterative improvement strategy to approximate the optimal path. Compared with the traditional deterministic search algorithm, the heuristic intelligent search algorithm is more flexible and adaptable in the search process by using the characteristics of heuristic function and randomness, which helps to overcome the complexity of the problem and find a better solution.

#### *3.1.1. ACO Algorithm*

In the ACO algorithm, the path in the ' pheromone' set has a heuristic effect on searching for the next node [43]. The principle of the algorithm is that the ant foraging tends to choose the path of the ' pheromone ' set. The idea is applied to the path planning as the ACO algorithm. The schematic diagram of the algorithm is shown in Fig. (**5**).

ACO algorithm has strong robustness and applicability, and is suitable for solving various combinatorial optimization problems [44]. Its applicability is mainly reflected in its ability to adapt to the dynamic changes of the problem space and different search environments [45]. Another typical advantage of ACO algorithm is that it can be implemented in parallel in distributed systems, and multiple subsystems can exchange pheromones with each other. However, as a heuristic algorithm, the performance of ant colony algorithm is greatly affected by parameter setting, and it needs to be adjusted repeatedly to obtain better results. In addition, the convergence speed of the algorithm is slow, especially there is a negative correlation between the global optimization ability and the convergence speed, and it is easy to fall into the local optimal solution problem.

The improved algorithm mainly improves the optimization ability of the algorithm from the aspects of algorithm structure, parameter selection and optimization, and combination with other intelligent algorithms [46]. Ant Colony System (ACS) and the meta-heuristic ant colony optimization algorithm (ACO-MH) proposed by Dorigo *et al.* have improved the algorithm structure [47, 48]. These algorithms provide a general algorithm framework for solving complex problems, but generally lack flexibility. In order to avoid falling into local optimum, Jiao *et al.* proposed a polymorphic ant colony optimization algorithm for path planning,

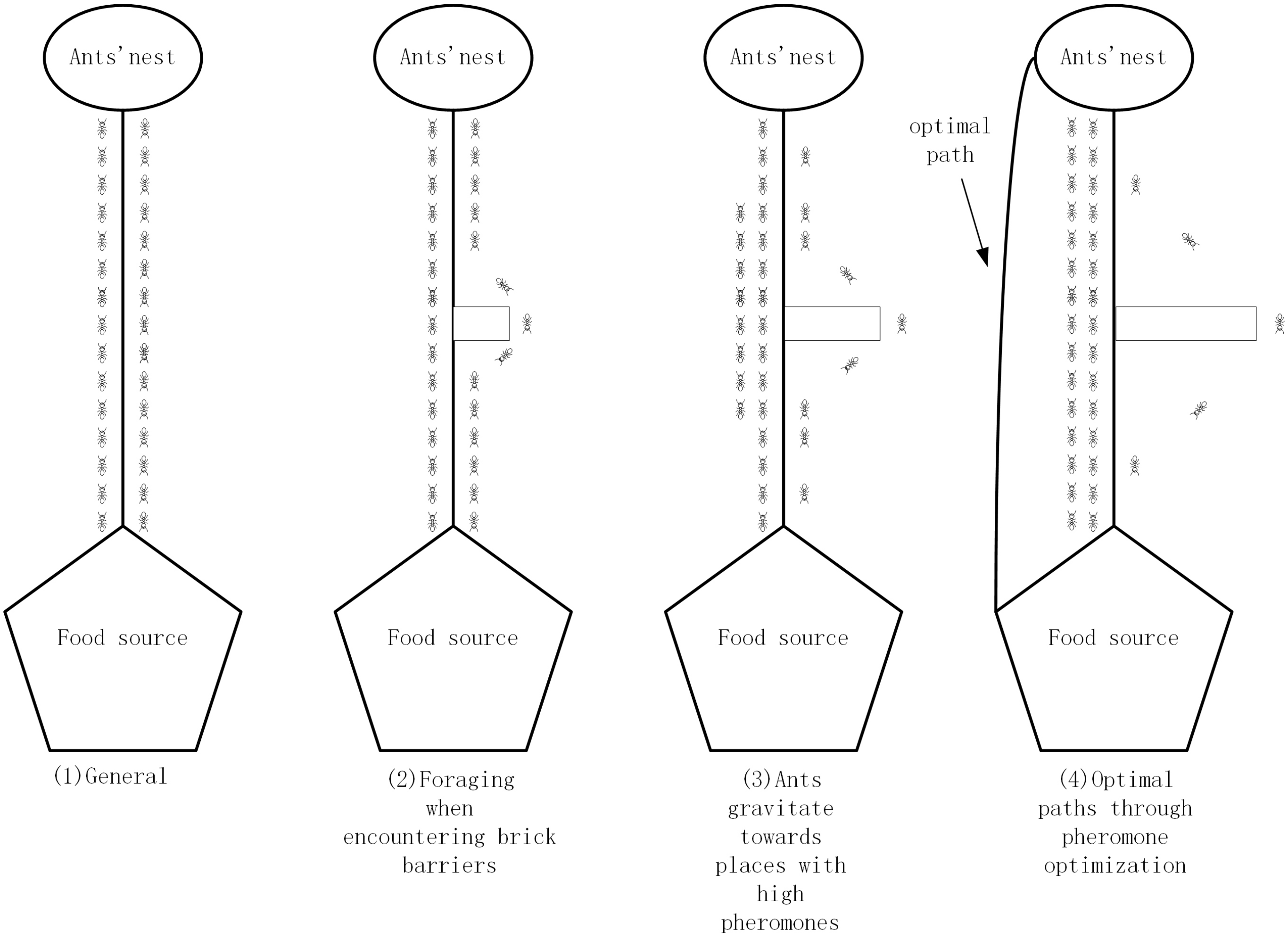


**Fig. (5).** Schematic diagram of the ACO algorithm. *(A higher resolution / colour version of this figure is available in the electronic copy of the article)*.

using adaptive state transition strategy and adaptive pheromone update strategy to ensure the relative importance of pheromone intensity and heuristic information in the iterative process [49]. Mahi *et al.* designed a hybrid algorithm based on particle swarm and ant colony, using particle swarm optimization to optimize the main parameters of ant colony algorithm, so as to improve the search efficiency and the computational efficiency of the algorithm [50]. In the literature, the problem is divided into two stages: the first stage uses the fast reverse gradient method to obtain the possible optimal solution; in the second stage, ACO algorithm is used to further improve the quality of the solution [51].

In the practical application of ant colony algorithm. An improved algorithm considering the rotation angle and the actual distance of the target, and using the actual distance as the selection probability parameter for path planning [52]. In the multi-robot path planning task, Li calls the improved K Means clustering algorithm for clustering tasks, so that the balance of energy consumption is better, and the overall performance is better than the basic ant colony algorithm [53].

### *3.1.2. Genetic Algorithm*

Genetic algorithm (GA) is a method of searching for the optimal solution by using genetic operators to select, cross and mutate to simulate the natural heredity and evolution of organisms in adapting to the environment [54, 55]. The biggest advantage of this algorithm is that it can be well integrated with other algorithms while giving full play to its own iterative advantages [56]. Therefore, by introducing the mechanism of randomness, diversity, parallel search and evolutionary optimization, genetic algorithm has better global search ability, better ability to overcome local minima, and can effectively deal with the optimization and search tasks in complex problems. However, the operation rate of genetic algorithm is low and takes up a lot of resources, and the application under initial conditions is not as good as ant colony algorithm. The steps of genetic algorithm in path planning are shown in Fig. (**6**) [57].

In order to improve its performance, many scholars have proposed different improvement methods in recent years. Aiming at the problem of slow convergence rate and poor

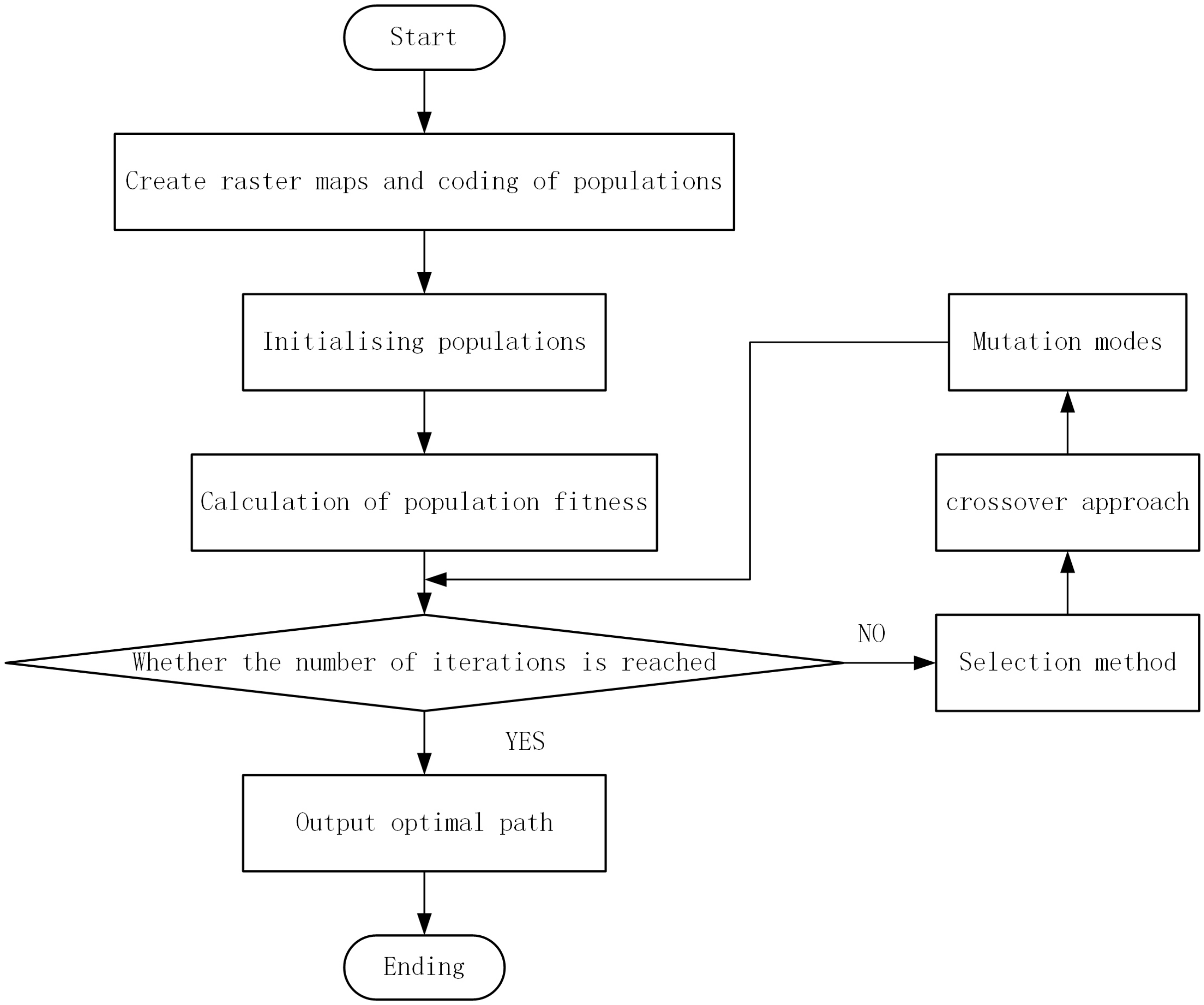


**Fig. (6).** Genetic algorithm path planning flowchart.

local search ability, Wang *et al's* improved method is to improve the search efficiency by improving the fitness evaluation index, which effectively shortens the average path length and reduces the number of iterations [58]. Aiming at the problem that the optimal solution cannot be found by multiple iterations of the initial solution due to the influence of the size of the environment grid, Nazarahari *et al.* proposed a hybrid method for path planning of multiple mobile robots in a continuous environment [59]. After improvement, not only the collision-free path is determined, but also all robots can be found close to the optimal solution. Aiming at the shortcomings of poor convergence and ignoring the cooperation between populations, Qu *et al.* proposed an improved genetic modification operator based on co-evolution mechanism [60]. The improved algorithm can better avoid the local optimal problem and has faster convergence speed. In view of the deficiency that the crossover and mutation probabilities remain fixed during the evolution process, Wang *et al.* proposed a method to automatically adjust the crossover probability and mutation probability according to the fitness value, which can not only accelerate the convergence speed of genetic algorithm, but also effectively prevent the algorithm from falling into local optimum [61].

In practical applications, genetic algorithm is more dependent on prior knowledge. For example, Huang Meng designed crossover, insertion, deletion, smoothing and collision avoidance operators according to the characteristics of prior knowledge and application scenarios, which improved the search efficiency and ensured the convergence to the global optimal solution. It overcomes the shortcomings of standard genetic algorithm [62]. Algorithm fusion is also easy to integrate with other algorithms. For example, Xing Dongxu first uses genetic algorithm to speed up the convergence speed and improve the efficiency of path planning, and then uses ant colony algorithm to obtain the best inspection path and improve the accuracy of path planning results [63].

### *3.1.3. Particle Swarm Optimization Algorithm*

The particle swarm optimization (PSO) simulates the behavior of biological groups such as birds or fish in searching and optimizing problems [64]. It has the characteristics of easy implementation, simple calculation and few parameters [65]. The main drawback of the particle swarm optimization algorithm is the lack of rigorous mathematical proof in terms of convergence theory and parameter setting. Its application is mainly based on experience and experiments. In addition, different particle swarm topologies simulate different social situations and have their own scope of application. When dealing with problems, appropriate algorithms and topologies should be selected according to the characteristics of the problem and engineering experience.

By adjusting the parameters, the overall performance of the algorithm can be improved. For example, Ao set the inertia weight factor of particles with poor fitness value to zero in the iterative process, which further improved the convergence of the algorithm [66]. Clerc.M *et al.* introduced the compression factor into the particle swarm optimization algorithm, so that the particles have the opportunity to search different regions in the space and obtain high-quality particles [67]. The experimental results show that it greatly improves the convergence speed and convergence accuracy of particle swarm optimization. Zhang proposes a non-linear dynamic adjustment method of inertia weight for the problems existing in the traditional particle swarm optimization algorithm [68]. At the same time, the concept of smoothness and safety is introduced into the fitness function. This method can significantly reduce the probability of the algorithm falling into local optimum.

Some scholars have also introduced better ideas from other algorithms from the perspective of improving the algorithm itself to improve performance. Jia introduced the hen update equation and the chick update equation in the chicken swarm algorithm to perturb the search stagnant particles, so that the disturbed particles are close to the global optimal solution, which verifies that the improved algorithm has the advantages of high optimization accuracy and good robustness in problem optimization [69]. Ding proposed a particle swarm optimization algorithm with genetic factors [70]. By referring to the idea of genetic algorithm crossover and mutation, the particles are operated to increase the population diversity, effectively reduce the number of iterations of the algorithm and improve the convergence speed. Chen proposed an improved particle swarm optimization algorithm based on neural network [71]. The simulation results show that the improved particle swarm optimization algorithm can be applied to static and dynamic obstacle environments to quickly plan a collision-free smooth path. At present, the reference algorithms introduced by other scholars also include: krill herd algorithm, genetic algorithm, bat algorithm, firefly algorithm and differential evolution algorithm. Experiments also prove that there are different degrees of improvement and optimization. However, the shortcomings of particle swarm optimization, such as low convergence accuracy and search stagnation, are still the main research points.

In practical applications, particle swarm optimization is often combined with other algorithms to improve performance. For example, high macro force uses improved adaptive hybrid annealing particle swarm-dynamic programming to avoid the stagnation of traditional particle swarm optimization [72]. The patent combines PSO and DWA to achieve a dynamic path planning method that can shorten the path length and improve smoothness and real-time performance [73]. The patent combines the advantages of grey wolf algorithm and particle swarm optimization algorithm. The improved algorithm converges quickly and reduces the risk of falling into local optimum [74].

## 3.2. Stochastic

The common point of the random intelligent search algorithm is that it will perform path planning by establishing sampling points. The advantage is that it does not need to model the environment specifically, and can randomly explore appropriate path points in the environment. It can quickly plan and process high-dimensional space and adjust according to the collected information. However, due to the strong randomness, the planned path is often not the optimal solution, and secondary optimization is needed in practical application.

### *3.2.1. PRM Algorithm*

The PRM method based on random sampling technique approximates the free space by constructing an undirected graph, as shown in Fig. (**7**) [75]. This method transforms the planning problem in continuous space into topological space, which can effectively solve the path planning problem in high-dimensional space and complex constraints [76]. However, the PRM algorithm is very dependent on the initialization conditions, and the number of sampling points is too small, which may lead to the failure of path planning. In addition, because the graph structure generated by the PRM algorithm in the learning phase is based on the static environment, the adaptability to the dynamic environment is also limited.

Reducing planning time and improving path security is one of the basic research directions of the algorithm. Zou used the random node generation function to generate random nodes in free space [77]. Under the condition that the number of sampling nodes is constant, they can find a feasible path with fewer random sampling points, which improves the utilization rate of nodes and reduces the number of nodes in the path. Aiming at the problems of high computational cost and poor real-time performance of the PRM algorithm in complex environments, Ravankar proposed a PRM method based on hybrid potential and proved that the planning success rate of the improved algorithm is more than 95% in both global and local environments [78]. These two methods can be used as effective references to provide improvement ideas.

In order to solve the difficulty of the PRM algorithm in the narrow channel region, Liu proposed the PRM algorithm in the potential field, thereby increasing the number of sampling points in the narrow channel space and realizing the optimal path connection, but the use of repulsive magnetic field is easy to cause uneven sampling points [79]. Li

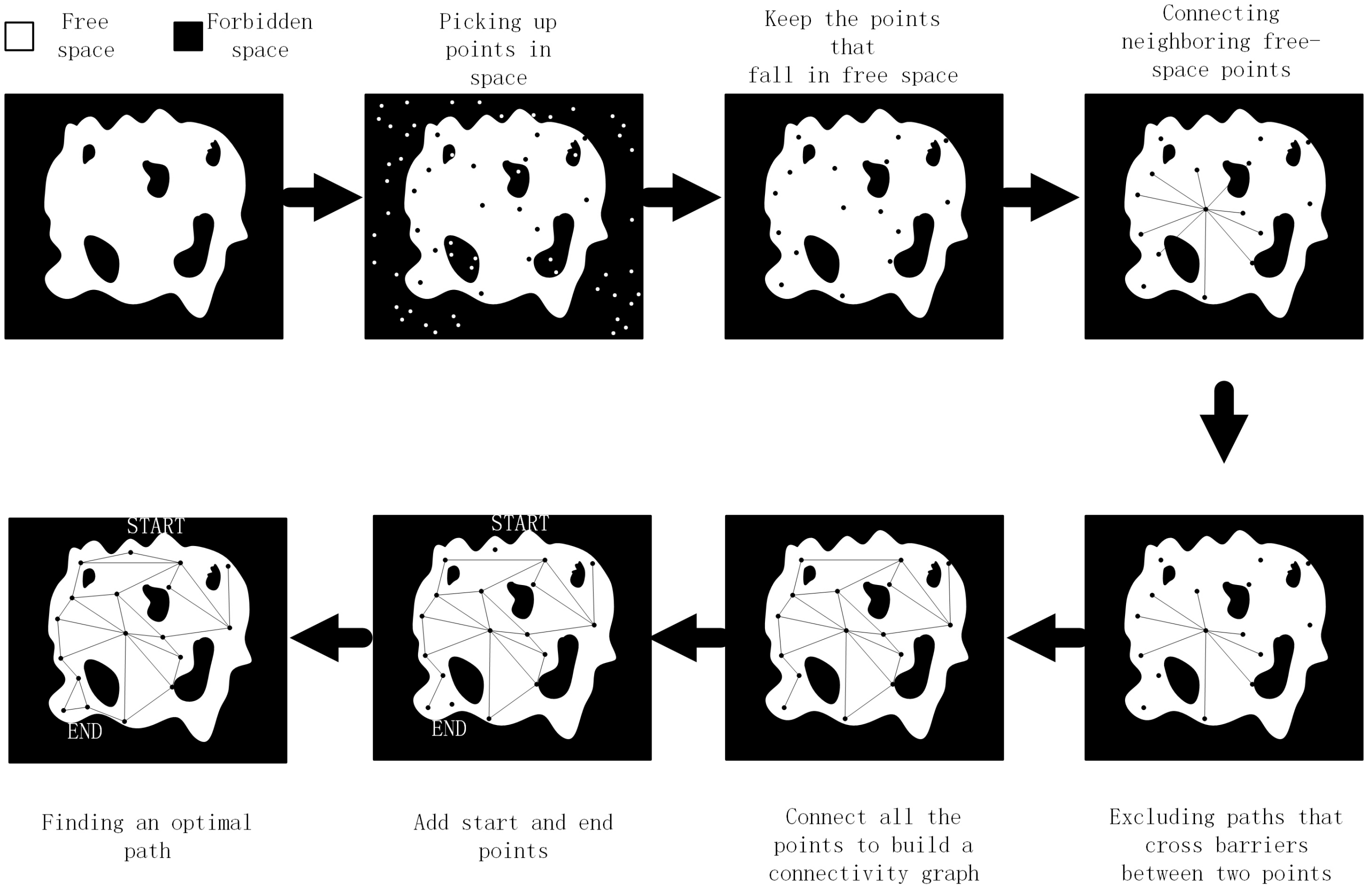


**Fig. (7).** PRM Connect. *(A higher resolution / colour version of this figure is available in the electronic copy of the article).*

proposed a PRM algorithm based on distance transform to obtain a reasonable distribution of sampling points [80]. These methods have a certain degree of representativeness, which effectively solve the narrow channel problem. Shortening the overall path length is also one of the research directions. Cheng uses the method of changing the distance of the connection points of the sampling points to reduce the unreasonable paths in the path network diagram, which effectively improves the efficiency and safety of the actual robot path planning [81]. Mohanta proposed a new probabilistic roadmap fuzzy control system, which makes the mobile robot turn smoothly at the sharp inflection point and find the optimal path in the environment with complex obstacles [82].

In practical applications, the PRM algorithm is often used as a preprocessing method to construct an undirected road map, and then other algorithms are used to obtain the shortest obstacle avoidance path. For example, patent [83] uses the Dijkstra search algorithm to search in the connected path map. Patent [84-86] uses the A * search algorithm to search on the undirected road map to obtain the shortest obstacle avoidance path. This method can significantly reduce the amount of computation and has the ability to find the optimal path.

### *3.2.2. RRT Algorithm*

In order to make up for the shortcomings of the PRM algorithm, Lavalle proposed a fast random expansion tree algorithm (RRT) based on sampling [87]. The algorithm has the advantages of fast exploration, strong robustness, strong adaptability to the environment, and can be used for real--time online planning. However, the computational complexity of RRT algorithm is higher than that of PRM algorithm, and the algorithm itself lacks optimization ability, which is not suitable for mobile robots to adopt directly. The extension process of RRT algorithm is shown in Fig. (**8**).

The main improvements to RRT in the existing literature are unidirectional random tree extensions, multidirectional random tree extensions, and fusion with other algorithms [88].

Among them, the one-way random tree expansion takes the starting point of the path as the root node of the random tree. The overall structure is simple, solves the problem of ' dimension explosion ', and can be well used for robot path planning with high-dimensional complete constraints such as manipulators and quadrotors. Frazzoli *et al.* proposed the RRT* algorithm with asymptotic optimality [89]. Based on the RRT node expansion, the random geometric graph and

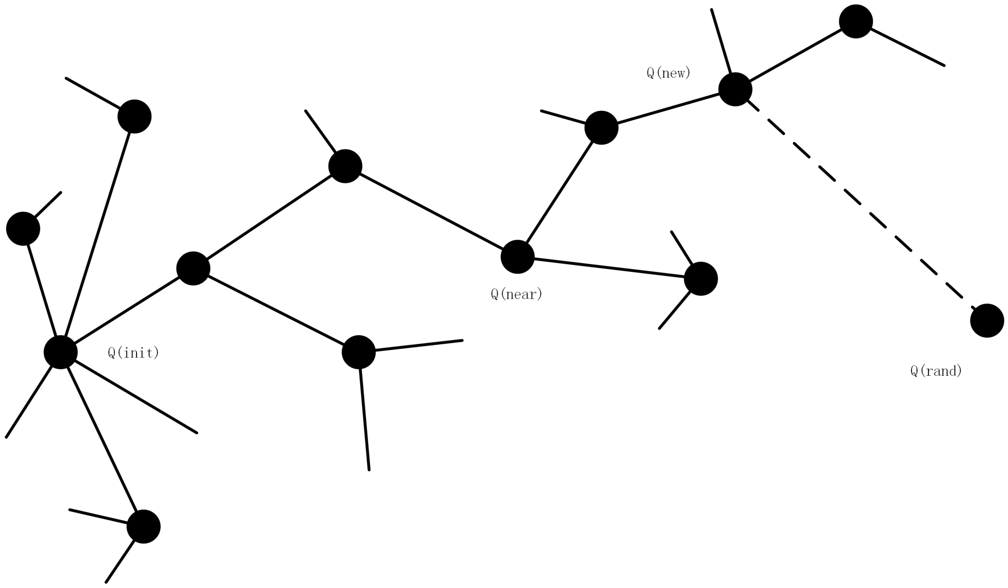


**Fig. (8).** RRT algorithm extension process.

pruning optimization theory are added to ensure that the nodes of the random tree can converge to the current optimal value. Nasir *et al.* proposed the RRT*-smart algorithm with intelligent sampling and path optimization functions, which alleviated the problem of slow convergence of RRT* [90]. However, intelligent sampling focuses on convergence speed and sacrifices random exploration characteristics, which may lose better solutions. Liu proposed a variable step size search based on RRT. Based on the idea of fast expansion of large step length and convergence path of small step length, the search efficiency is improved [91].

The multi-way random tree is extended with a one-way random tree as the basic tree structure. Multiple random tree root nodes are constructed in the workspace to optimize the connection between random trees. At the same time, the random search performance is strong, which is more suitable for path planning in narrow areas or complex environments. The patent discloses a bidirectional RRT path planning method. The algorithm alternately expands the nodes of the two path trees until the two path trees intersect, and smoothes the initial path to obtain the final path [92]. Qureshi proposed an optimal algorithm IB-RRT* for intelligent bidirectional search, which selects extended nodes by random node neighborhood filling or nearest node weight sorting, and is dedicated to complex environment search [93]. Burget *et al.* proposed a bidirectional search algorithm BI-RRT* that satisfies the task constraints [94]. The algorithm combines the characteristics of Informed-RRT* and B-RRT*, and uses a double random tree to generate the initial path to solve the problem of slow convergence speed. The algorithm is more efficient than the B-RRT* algorithm.

Integration with other algorithms can also effectively improve the planning ability of the RRT algorithm. For example, Jia proposed an improved algorithm that combines artificial potential field method with RRT algorithm [95]. This algorithm effectively solves the problem that RRT algorithm is easy to cause local minimum value, greatly improves and improves the planning efficiency. Higueras *et al.* used the fully convolutional neural network (FCN) to learn the path planning task in an unsupervised learning manner, avoiding the explicit expression of the cost function [96]. The trained FCN guided the RRT* extension to complete the actual path search. Experiments showed that FCN-RRT* achieved better results than RLT*. Chter *et al.* proposed a self-learning non-uniform node sampling distribution, the possible optimal path area is obtained by offline learning, and then the sampling algorithm is executed [97]. The sampling nodes are concentrated in this area for bias sampling to improve the path planning speed.

The patent considers the uncertainty of pose estimation in practical applications, provides pose estimation uncertainty constraints for trajectory planning in dynamic scenes, and improves the safety and real-time performance of robot trajectory online planning [98].

## 4. ARTIFICIAL INTELLIGENCE ALGORITHM

Artificial intelligence algorithm is a strategy based on machine learning, optimization or search to model the environment and learn the best path. It directly iterates with the environment to obtain the reward value to optimize the strategy, so as to realize the autonomous planning of the optimal path for mobile robots.

### 4.1. Q-Learning Algorithm

The Q-Learning algorithm is a reinforcement learning algorithm that uses a look-up table method to describe the value function Q(st, at) of the state-action pair, allowing the mobile robot to use the learning mechanism to plan a better collision-free path based on changes in the environment [99, 100]. But when the working environment is more complex, Q-table needs to occupy a lot of memory space, causing the "disaster of dimensionality" [101].

The traditional reinforcement learning method has no prior knowledge of the environment in the initial stage of learning [102]. In the application of navigation planning, there are often problems such as slow convergence speed and long learning time. In this regard, many scholars have emphasized the effect of using prior knowledge to guide during learning. FRAMLING *et al.* improved the rate of reinforcement learning by combining the concepts of short-term memory and long-term memory [103]. LILLICRAP use neural network to fit the Q function to improve the convergence stability of Q-Learning [104]. Duan proposed a definition method of environmental state space based on potential energy field knowledge, which can guide the mobile robot to converge quickly in the early stage of learning, improve the learning efficiency in the initial stage, and greatly improve the convergence speed of the algorithm [105].

To address the problem of slow convergence, it is also effective to improve the algorithm itself. Soong *et al.* proposed an improved Q-learning algorithm, which proves that properly initializing the Q value can accelerate the convergence speed of Q-learning [106]. Mao proposed an improved ε-Q-Learning algorithm. The results show that compared with the existing Q-Learning algorithm, the improved algorithm can not only find a better path, but also effectively reduce the cost of iterative search [107]. Bae *et al.* proposed a multi-robot path planning algorithm based on Q-learning and convolutional neural network (CNN) algorithm [108]. The experimental results show that this method enables multiple mobile robots to plan paths quickly and complete tasks efficiently in different environments.

The patent proposes an APF-DQN algorithm, which realizes the path planning process and the key node identification process simultaneously [109]. The patent proposes a path planning method based on Q-Learning algorithm for complex sequential logic tasks, which is more reasonable on the basis of reflecting the characteristics of signal sequential logic tasks, and makes the path planning results more reasonable and effective [110].

### 4.2. Deep Reinforcement Learning Algorithms

Reinforcement learning (RL) is limited by the dimension of action space and sample space, and it is difficult to adapt to complex problems closer to the actual situation. Deep learning (DL) has strong perception ability and can adapt to complex problems, but it lacks certain decision-making ability. Therefore, the combination of DL and RL to obtain deep reinforcement learning (DRL) and its application provides a new idea and direction for motion planning of mobile robots in complex environments [111].

The deep reinforcement learning algorithm is mainly divided into the algorithm based on the value function, the algorithm based on the strategy function and the Actor- Critic architecture algorithm combining the advantages of the two. The algorithm based on the value function has a network that fits the action value function, and the representative algorithms are DQN, Rainbow, *etc.* [112, 113]. The algorithm based on the strategy function has a strategy network that fits the probability distribution function of the action space, and the representative algorithms are PG, TRPO, *etc*. The Actor-Critic architecture algorithm combining the advantages of the two has both a Critic network that evaluates the quality of the action and an Actor network that selects the action. Its representative algorithms are A3C, DDPG, *etc* [114-116].

Currently, the application and improvement of DRL in path planning is one of the main research hotspots: Kulkarni *et al.* proposed a hierarchical DQN algorithm (hierarchical-DQN, h-DQN), which divides the control task into several levels and learns from multi-level strategies [117]. Each level is responsible for controlling at different time and behavior abstraction levels, which improves learning efficiency. Zhu *et al.* solved DRL 's lack of generalization ability to new targets through the Actor-Critic model and proposed the AI2-THOR framework, which improved the problem that DRL could not be transferred from the simulated environment to the real world [118]. Wang *et al.* proposed a selective training mode based on the minimum depth information, and combined with the A3C algorithm to train the robot, which improved the path-finding ability of the robot in an unknown complex environment [119]. Gao *et al.* proposed a fusion algorithm that combines the dual-delay deep deterministic strategy gradient of the deep learning algorithm with the probability roadmap [120]. The experimental results show that the algorithm improves the generalization ability of the model. Foerster *et al.* proposed a multi-robot behavior-criticism method, which enables each agent to make decentralized decisions while increasing the common reward value of all agents, and significantly improves the average performance of robot path planning [121].

Deep reinforcement learning is also widely used in real life. Patents solve the problem that endoscopic path planning cannot be combined with the key information of the inspection site, and improve the accuracy of endoscopic path planning [122]. The patent applies the deep reinforcement method to the warehouse management system, which greatly improves the real-time performance of the warehouse management planning path and ensures the efficient operation of the warehouse management [123].

At present, the research on three-dimensional path planning based on deep reinforcement learning mainly focuses on obstacle avoidance strategy. For all kinds of obstacles, the same way is used to avoid them, and there is still a certain deviation from the actual optimal path.

## 5. LOCAL OBSTACLE AVOIDANCE ALGORITHMS

Local path planning is mainly to perceive the surrounding environment information in real time through various sensors (such as camera, lidar, millimeter wave radar, ultrasonic radar, inertial navigation, *etc.*) carried by itself. After obtaining the local obstacle distribution, the local optimal path without collision is planned in real time. The commonly used local path planning algorithms include time elasticity band method, artificial potential field method and dynamic window approach method.

### 5.1. Artificial Potential Field Methods

Artificial Potential Field methods (APF) is a virtual force method [124]. It constructs a gravitational field and a repulsive field that work together around the target position and the obstacle, and then plans a collision-free optimal path by searching the descending direction of the potential function [125]. The algorithm has simple structure, good real--time control and smooth planning path, which is suitable for local path planning [126].

The algorithm has two main types of limitations due to its own principles. The first is the problem of target unreachability, and the second is the problem of local minima [127]. Improvements for these two types of shortcomings mainly lie in three directions: improving or utilizing new potential field functions, eliminating or avoiding local minima, and combining with other algorithms [128].

In terms of changing the potential field function, Geva *et al.* solved the target unreachable problem by adding a dynamic repulsion gain factor to the repulsion potential field function [129]. The value of the factor can be dynamically adjusted by the fuzzy controller. Chen *et al.* proposed adding the relative angle, speed and acceleration of the robot and the obstacle as constraints to improve the potential field function, effectively solving the problem of target unreachability caused by falling into local optimality, but the time to solve the problem is too long [130].

To solve the problem of local minimum point, we mainly guide the AUV to escape from the local minimum point by setting up virtual guidance points [131]. Azzabi *et al.* proposed a new repulsive potential function, which can activate the virtual escape force when the local minimum value is detected, so that the robot can get rid of the deadlock position and smoothly avoid the obstacles in the target direction [126]. In order to get rid of the complexity of adding guide points, Milad *et al.* proposed a potential field filling strategy to avoid local minimum points, that is, to search for the global [59]. If a local minimum point is found, the potential field of this point is filled to eliminate the local minimum point.

Combined with other algorithms, it not only retains the advantages of simple principle and rapid response of artificial potential field method, but also overcomes the shortcomings of the algorithm itself to a certain extent, and further optimizes the obstacle avoidance path [132]. Duan *et al.* proposed a parallel search method combining artificial potential field model with genetic algorithm [133]. The improved algorithm can avoid obstacles and find the best path of mobile robot in complex environment. The patent proposes an artificial potential field path planning method that combines gradient descent and beetle antennae search, which can make the planned path conform to the robot dynamics constraints, smooth the path, and break through the local optimum [134]. Abdalla combines the improved artificial potential field algorithm with fuzzy logic [135]. The fuzzy logic controller is used for the motion control of the mobile robot, and the membership function is optimized by PSO algorithm. The simulation results show that the robot can navigate in a smoother path, react faster, and avoid obstacles effectively in both static and dynamic environments.

The patent discloses a method of information fusion of laser point cloud and video image, and local path planning of obstacle avoidance path based on improved artificial potential field algorithm, so as to better avoid ship collision [136].

### 5.2. Dynamic Window Approach

The Dynamic Window Approach (DWA) is a method that samples the surrounding at the current moment [137]. The algorithm performs real-time path planning based on the robot's constraints and environment information. It can avoid obstacles and find suitable paths in complex environments, while also avoiding collisions with obstacles in the search space. However, it is highly dependent on global parameters and is not applicable to unknown environments [138]. In practical applications, other algorithms are usually combined to achieve a complete path planning process [139, 140].

Fig. (**9**) is a schematic diagram of DWA. The AGV is represented by a black boat, and obstacles are represented by gray rectangles. The curve in the figure represents the movement trajectory of the AGV.

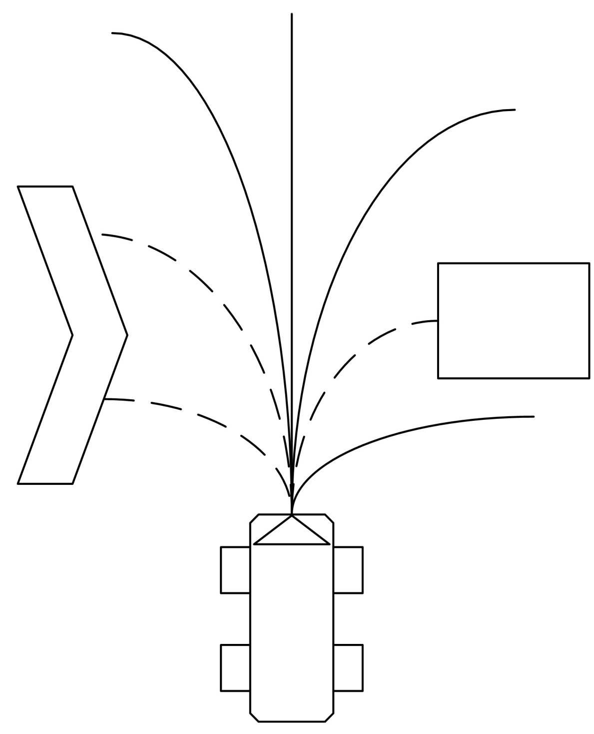

**Fig. (9).** Schematic diagram of DWA.

Although the application of dynamic window method for path planning makes the mobile robot have good obstacle avoidance ability and the path is relatively smooth, it is easy to fall into the local optimal solution and cannot reach the specified target along the global optimal path. LI *et al.* proposed an improved dynamic window method, which considers the relationship between the size of the mobile robot and the feasible space between obstacles, so that the algorithm can solve the local minimum problem and improve the smoothness of the path [141]. Based on the traditional dynamic window algorithm, EDUARDO *et al.* proposed the moving obstacle dynamic window method (DW4DO) and the moving obstacle tree dynamic window method (DW4-DOT) to deal with dynamic obstacles, which improved the security and stability of the algorithm [142]. MISSURA *et al.* added a dynamic collision model to the dynamic window method to predict future collisions with the environment, which not only keeps the algorithm computationally efficient, but also reduces the number of collisions in a dynamic environment [143].

In terms of algorithm fusion, Chang *et al.* proposed an improved DWA algorithm based on Q-learning to solve the problem of insufficient DWA evaluation function, which leads to high dependence on global reference [144]. The algorithm modifies and extends the evaluation function on the basis of the original DWA algorithm, and adds two evaluation functions to improve the navigation performance. This method shows high navigation efficiency and success rate in complex unknown environment.

In practical applications, the dynamic window method is rarely used as the only path planning method. It is generally used as a local planning algorithm and other algorithms. Only when the planning pressure is small, it is used as an obstacle avoidance algorithm, such as a patent [145].

### 5.3. Time Elasticity Band Method

The Temporal Elasticity Band (TEB) method is an improved algorithm based on the Elasticity Band (EB) algorithm [146, 147]. The time elastic band method explicitly enhances the ' elastic band ' and time information, thus allowing the dynamic constraints of the robot to be considered and the trajectory to be directly modified, and path optimization to be performed within the band [148]. The advantage of the TEB algorithm is that it takes into account the time factor and can generate trajectories based on the speed and acceleration of the robot to provide a smoother and safer path [149]. However, in the practical application process, there are still problems such as speed jumps and robot vulnerability to shocks. The trajectory composed of the pose of the continuous robot is shown in Fig. (**10**).

In response to the problem of unstable speed output, Chen *et al.* proposed a TEB-VO trajectory planning algorithm that integrates the TEB algorithm and the velocity obstacle method (VO), and dynamically adjusts the discrete intervals of the planned trajectory and the maximum linear speed allowed by the robot [150]. Experiments show that the algorithm has good trajectory planning and dynamic obstacle avoidance ability. In the process of trajectory optimization, Zheng *et al.* constructed a specific improved TEB algorithm with acceleration constraints [151]. The experimental results show that the improved TEB algorithm is suitable for the Ackerman robot, and the planned trajectory is better.

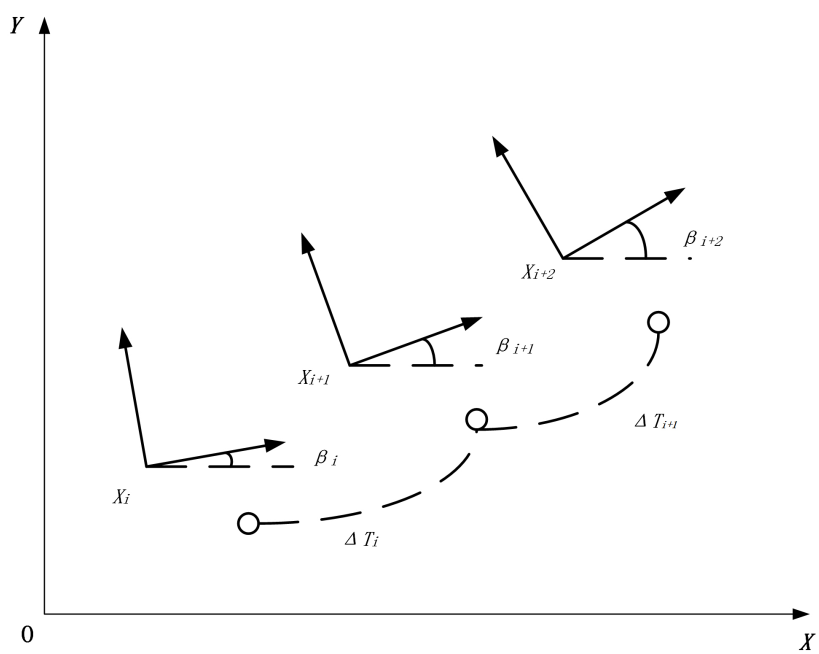


**Fig. (10).** Trajectory continuous position sequence with time interval. *(A higher resolution / colour version of this figure is available in the electronic copy of the article)*.

**Table 1. Summary of mainstream path planning algorithms.**

| Algorithms | | | Implementation Mechanisms and Principles | Cutting Edge | Limitations |
|---|---|---|---|---|---|
| Conventional planning algorithm | Bug | | Move towards the target point and go around obstacles. | Fast planning speed; suitable for real-time path planning | Only applies to 2D space; local minima problem exists |
| | GM | Dijkstra | Solve for the distance between the vertices of the right graph | Good robustness; fast computation speed | Planning is inefficient when the number of nodes in the graph is too large. |
| | | A* | Find the minimum estimated cost from the current node to the goal point | Simple calculation; short planning path | High computational effort; more inflection points in paths |
| | | D* | Find the minimum integrated cost from the current node to the goal point | Faster computation and shorter planning paths | Paths are closer to the edge of the obstacle; there are many turning points in the paths |
| | VFH | | Move in the direction of low obstacle density | High reliability, computational efficiency and robustness. | Not applicable to narrow regions; local minima problem exists |
| | Voronoi | | Connecting boundaries at a certain distance from an obstacle to form a path | Longer distance to obstacles; high safety | Not applicable to high-dimensional spaces; high path cost |
| Intelligent search algorithm | Heuristic | ACO | Ants move to places with high pheromones | High robustness | Easy to fall into local optimality |
| | | GA | Populations produce new species through crossover and mutation | Strong asymptotic optimality; overcoming local optima | Low computing speed; high memory usage |
| | | PSO | Individual and group collaboration and information sharing | Easy to implement, high robust, good results on continuous space optimisation problems | Prone to premature convergence, search performance is highly dependent on parameters; Prone to local minima |
| | stochastic | PRM | Constructing path network graphs using random sampling in the workspace | Simplified analytical computation of the environment, suitable for the planning of high-latitude free bitmap spaces | Computationally intensive; not applicable to online planning |
| | | RRT | Random trees are growing and spreading in all directions | Applicable to high dimensional spaces; relatively simple algorithm; fast scaling; applicable to differential constraints | High stochasticity; high path cost; decreasing efficiency with increasing environmental complexity |
| Artificial intelligence algorithm | Q-Learning algorithm | | Reward and punish actions through interaction with the environment | Convergence is guaranteed without knowing the model | Not suitable for complex work environments |
| | Deep Reinforcement Learning Algorithms | | Self-learning intrinsic laws of path planning samples and planning feasible movement paths | Strong perceptual skills and ability to adapt to complex problems | All obstacles are avoided in the same way, which still deviates from the optimal path in reality |
| Local obstacle avoidance algorithms | APF | | Changing the direction of robot motion by combined forces | Simple structure;capable of avoiding obstacles in real time | Prone to target unreachability and local minimum problems |
| | DWA | | Sampling of speed and motion parameters and positions | It is possible to reach the target point quickly and at the same time avoid collisions between the robot and obstacles | Highly dependent on global parameters, not suitable for unknown environments |
| | TEB | | Plan paths with fewer obstacles and include time information | Generate trajectories based on robot speed and acceleration | Problems with velocity jumps and robot vulnerability to shocks |

Wen Yu *et al.* proposed an improved TEB algorithm that increases the risk penalty factor constraint in order to solve the problem that traditional TEB algorithm planning is prone to abnormal behaviors such as regression and large turns in cluttered scenes [152]. Experiments show that the improved TEB algorithm can plan safer and smoother trajectories in complex environments and reduce the impact on the robot. Aiming at the defect that the TEB algorithm cannot distinguish the types of obstacles, Xie *et al.* proposed an improved TEB algorithm using two mean filters to filter the laser point cloud [153]. Experiments show that the dynamic obstacle avoidance trajectory planning system based on the improved TEB algorithm can perform real-time trajectory planning in complex dynamic environments.

In the aspect of algorithm fusion planning, Guo *et al.* proposed a multi-task navigation scheduling algorithm based on A* and TEB [154]. The improved A* algorithm avoids the phenomenon of crossing obstacles and controls the rotation angle of adjacent path points within 45°. The improved TEB algorithm reduces the velocity and angular velocity variance of the robot by 47.1% and 18.2% respectively. Shen proposed a hierarchical path planning method, which combines the improved A* algorithm with the TEB algorithm. The improved A* algorithm can reduce the turning point by 93.69% and shorten the path length by 0.9% [155]. The improved TEB algorithm can reduce the degree of deviation from the global path, and the fusion of the two can effectively avoid unknown obstacles.

In practical applications, it is mostly used in occasions with high sensitivity to time and high safety. It is used in conjunction with global planning algorithms such as A* as local planning algorithms, such as patents [156, 157].

## 6. COMPARISON OF PATH PLANNING ALGORITHMS

This paper briefly summarizes the current mainstream path planning algorithms, and lists the implementation mechanisms, principles, advantages and limitations of related algorithms. The results are shown in Table **1**.

The existing path planning algorithms can be adeptly applied to mobile robots, as each algorithm possesses its unique advantages and applicable scenarios. However, their development is often constrained by inherent limitations, necessitating substantial efforts in algorithm optimization. In practical applications, it is difficult for a single mobile robot path planning model to simulate the changing reality, and multi-mobile robot path planning is closer to reality. Multi--mobile robots have problems such as collaboration and task scheduling, so reasonable planning is needed to improve planning efficiency and reduce energy consumption.

Compared with other path planning algorithms, the network architecture of artificial intelligence algorithms often enables algorithms to have strong environmental adaptability. With the increase of mobile robot application scenarios, the complexity of the working environment it faces is further increased, and the advantages of artificial intelligence algorithms will be further demonstrated. Therefore, it is of great significance to apply deep reinforcement learning to mobile robots. In the future work, a lot of research needs to be done on this application scenario.

At the same time, the algorithm evaluation functions in different scenarios are different, which is difficult to be expressed by accurate mathematical models. In the known applications, obstacles are approximately equivalent to circles, rectangles, *etc.,* and then path planning is performed on the environment. The generalization ability in practical applications needs to be improved.

## CONCLUSION

Path planning technology is an important branch in the field of intelligent mobile robots, and the use of effective path planning methods can enhance efficiency, save time, and reduce the utilization of human and material resources. The current path planning algorithms have certain limitations and still require a lot of work to improve their performance and applicability. With the development of artificial intelligence technology, multi-technology integration provides opportunities for the advancement of path planning algorithms. By improving the performance and applicability of the path planning algorithm, the application scenarios of mobile robots can be broader.

## CURRENT & FUTURE DEVELOPMENTS

This paper delves into mobile robot path planning algorithms, categorizing them into four distinct groups: traditional planning algorithms, intelligent search algorithms, AI-based algorithms, and algorithms designed for local obstacle avoidance. Following this classification, the paper explores their respective advantages and application domains. Subsequently, drawing from current research and future trends identified by scholars, the main focuses of contemporary mobile robot technology research are summarized as follows:

### 1. Optimizing the Performance of Existing Algorithms

Despite the existing algorithms having inherent limitations, rendering them unsuitable as general-purpose solutions across various scenarios, they still find application in specific contexts. The underlying mathematical principles remain desirable. Therefore, optimizing path planning algorithms with consideration to their limitations becomes crucial. Future work should delve into exploring and applying additional mathematical theories to enhance these algorithms. Examples include refining the initial parameter setting of ACO, improving the cost function of A* and D* algorithms, and enhancing the evaluation function of the DWA algorithm.

### 2. Multi-sensor Information Fusion

The rapid development of sensors has led to a trend towards multimodal sensor fusion in mobile robotic systems. In the process of path planning and obstacle avoidance, the basis is map modeling and identification of obstacles through the collection of information about the surrounding environment. This involves the effective integration of information collected by individual sensors. The purpose of multi--sensor information fusion is to eliminate redundant information from the data and provide a basis for reliable analysis, thereby improving accuracy. It is also necessary to compare the data and automatically exclude erroneous data information to ensure that reliable environmental sensing results are obtained. Effective multi-sensor fusion therefore improves the accuracy of maps and provides more accurate environment sensing for mobile robotic systems, leading to more reliable, safe, and efficient path planning and obstacle avoidance capabilities.

### 3. More Efficient Algorithmic Fusion

Path planning has become relatively mature in the present day and can already be applied in production life. However, each algorithm has its own advantages and disadvantages, such as local minima, path inflection points, and low planning efficiency. The fusion of multiple algorithms can enhance strengths and mitigate the shortcomings of the planning method, ultimately achieving higher efficiency. The use of neural networks in the PRM algorithm for sampling point learning and prediction can help generate optimal solutions and reduce the generation of invalid sampling points. This ultimately accelerates the convergence speed of the algorithm. The fusion of the A* algorithm and the ant colony algorithm, along with the introduction of the evaluation function of the A* algorithm, optimizes the pheromone updating method of the ant colony algorithm. This not only speeds up the convergence rate of the algorithm but also overcomes the problem of local minima. Therefore, a more efficient fusion path planning algorithm is also a key research objective for future path planning.

### 4. Wider Range of Applications

In the current application scenario, most mobile robots realize the path planning function through their computing units. With the increase in market demand, mobile robots are being applied to a variety of complex scenarios. This trend highlights the inevitable need for high-performance core processing units in mobile robots. And backed by the development of Internet of Things technology, data can be transmitted quickly through the Internet. Therefore, it is also a trend to transfer the large amount of data that mobile robots need to process to high-performance remote servers through the network.

For example, while traditional driverless cars can only achieve autonomous path planning through high-speed computing modules equipped with high-speed capabilities, it is now possible to process a large amount of data collected by multiple sensors in real-time through network collaboration, IoT, and other technologies. This method involves transmitting the information collected by the sensors to a cloud server in the IoT *via* a 5G odule. Loud server combines high-precision maps and large amounts of data to plan a safe and collision-free path using local obstacle avoidance algorithm. The planning results are then sent back to the mobile robot for execution.

## AUTHOR'S CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: study conception and design: W. Liu, J. Peng, S. Liu, H. Liu, X. Yang; draft manuscript: L. Wang. All authors reviewed the results and approved the final version of the manuscript.

## LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| GM | = | Grid Map |
| VFH | = | Vector Field Histogram Method |
| ACS | = | Ant Colony System |
| PSO | = | Particle Swarm Optimization |

## CONSENT FOR PUBLICATION

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## CONFLICT OF INTEREST

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