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Obstacle Avoidance Motion in Mobile Robotics

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Keywords

mobile robot, obstacle avoidance motion, global path planning, local obstacle avoidance

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Tang Yunchao: Named as one of the "Global Top 2% Scientists" by Elsevier in 2021 and 2022, reported as a featured scientist on CCTV-10's "Innovation Time" program, Dr. Tang specializes in research on robotics, structural information perception, and intelligent construction. He has led five national, provincial, and ministerial-level projects, including the National Natural Science Foundation and Postdoctoral Foundation, as well as over 20 projects at the departmental and corporate level. As a first/corresponding author, he has published over 40 SCI papers, including 9 ESI hot papers, with an h-index of 33. Dr. Tang has been awarded six prizes, including the first prize in the Guangdong Province Science and Technology Award for Measurement, Control, and Instrumentation. He serves as an editorial board member for five SCI journals, including Frontiers in Materials, Journal of Sensors, and Buildings, and guest editor for several SCI top-tier journals.

Obstacle Avoidance Motion in Mobile Robotics

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Abstract: The advancement of artificial intelligence technology has significantly enhanced the utilization of mobile robots in various fields such as industry, aerospace, and agriculture. The autonomous obstacle avoidance capability of these robots is crucial to the safety and efficiency of their operations in diverse settings. Path planning, a key technology in obstacle avoidance, plays an essential role in the overall performance of these systems. This paper presents a comprehensive review of path planning technology for mobile robots, categorizing the algorithms into global planning and local obstacle avoidance according to their operational requirements. Specific focus is given to the global planning methods involving sampling, graph search, and biomimetics, assessing their convergence rate, memory demands, and computational efficiency, along with strategies for improvement. The paper then explores local obstacle avoidance algorithms, explicating their foundational principles, characteristics, and ideal use cases. In conclusion, the paper synthesizes the state-of-the-art in autonomous obstacle avoidance, noting that the strategic integration of various algorithms to refine planning performance, and the enhancement of traditional algorithms' intelligence is projected to be a leading trend in future research.

Keywords: mobile robot; obstacle avoidance motion; global path planning; local obstacle avoidance

移动机器人避障运动研究

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摘要：随着人工智能技术的飞速进展，移动机器人在工业、航天及农业等领域的作用逐渐凸显，其自主避障能力直接关系到在不同环境中作业的安全性与效率，而路径规划作为避障的核心技术

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之一，在决定避障性能方面起着至关重要的作用。对移动机器人路径规划技术进行了综述。基于作业需求将算法分为全局规划和局部避障两类。详述了以采样、图搜索和仿生学为基础的全局规划方法，分析了其收敛速度、内存需求及计算效率，并探讨了其改进策略。对局部避障算法进行了探讨，概述了其原理与特点，并明确其最佳应用场景。对当前的自主避障技术进行了总结，强调了传统算法的智能化程度仍需提升，以及集成不同的算法以提高规划性能将是未来的发展大势。

关键词：移动机器人；避障运动；全局路径规划；局部避障算法

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0 Introduction

Mobile robots are assuming an increasingly vital role in various domains, encompassing daily life, industrial production, military operations, and disaster relief. To enable the autonomous operation of robots in intricate environments, obstacle avoidance technology assumes paramount importance [1-5]. Path planning algorithms are at the core of the autonomous obstacle avoidance movement of mobile robots and play a key role in ensuring accurate obstacle avoidance of mobile robots in complex and unfamiliar environments. They involve the robot autonomously charting a collision-free course from the initial point to the target point by assimilating available environmental data, its own positional information, and task requisites through the selection of appropriate algorithms. Path planning algorithms, to a significant degree, ascertain the precision and efficacy of obstacle avoidance motion [6-9].

This paper presents a comprehensive overview of path planning algorithms for mobile robots. To begin, path planning is categorized into global planning and local obstacle avoidance based on the operational prerequisites of mobile robots. Subsequently, predicated on the theoretical underpinnings and features of path planning algorithms, global planning is further subclassified into sample-based methods, graph search-based methods, and bio-inspired intelligent approaches. Following this, the paper delves into local obstacle avoidance algorithms and compares the merits and demerits of diverse path planning algorithms. Finally, the paper furnishes a summary of path planning algorithms for mobile robots, alongside a discussion of future developments in this domain.

1 Path planning method of mobile robots

Path planning refers to the autonomous planning of a safe and collision-free route from an initial position to a target position by a mobile robot. Path planning algorithms can be categorized into global and local planning. Global path planning algorithms are suitable for the case where the information of the objects in the environment is known, and the positions of the objects remain stationary, which mainly include sample-based search methods, graph search-based strategies, and bio-inspired intelligence algorithms. However, in the real world, mobile robots often have to navigate through unknown and intricate environments, and traditional global path planning algorithms fail to meet the obstacle avoidance requirements. Therefore, it is necessary to incorporate local obstacle avoidance algorithms to ensure that mobile robots can bypass obstacles and reach the target location. This paper presents an overview of both typical global path planning algorithms and local obstacle avoidance methods, as illustrated in Fig. 1.

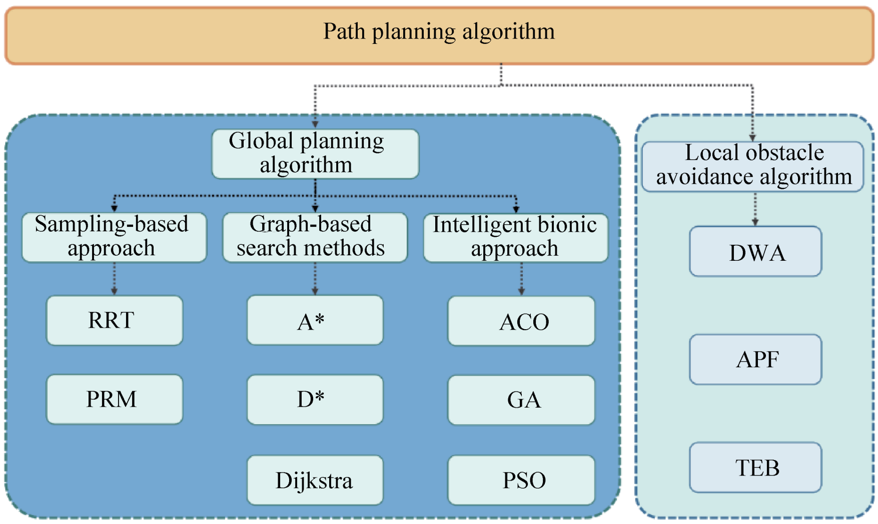

Fig. 1 Path planning algorithm classification

1.1 Global path planning algorithm

1.1.1 Sampling-based path search method

The sampling-based approach imposes minimal requirements on the overall map environment representation, making it suitable for scenarios with unknown environmental information. This method randomly samples points on the map and connects them to form potential paths. A collision detection algorithm assesses the feasibility of the paths between adjacent sample points. If a path avoids obstacles, it is considered feasible, and this process continues until a path reaching the target position is established. The main sampling-based methods include the probabilistic roadmaps method (PRM) and the rapidly exploring random tree (RRT) method.

(1) RRT algorithm

Lavalle's RRT algorithm, proposed in 1998 [10], starts with an initial position as the root node and employs a random distribution function to sample child nodes within a predefined map. Nodes adhering to specific criteria are added to the random tree through collision detection methods until the destination point is reached. The algorithm then identifies a collision-free trajectory connecting the start and end points within the constructed random tree. RRT's simplicity, adaptability, and suitability for real-time path planning have gained significant recognition. However, its random spatial expansion hinders directionality, leading to reduced efficiency and path quality.

To address these limitations, various improvement methods have been proposed. These include guiding the random tree growth using obstacle and target point information to enhance efficiency [11], employing the bi-directional expansion strategy (Bi-RRT) [12], and re-selecting parent nodes for wiring, as seen in RRT* [12]. Since the traditional RRT algorithm blind search leads to increased computational effort and low search efficiency, in response, some scholars have guided the random tree growth by adding guidance information such as artificial potential fields (APFs) [13-14], obstacles, and targets [15] to the search space. In the optimization process of the RRT algorithm, the evolution of the RRT algorithm reflects the application of innovative optimization strategies for specific challenges. The integration of APFs [16] enables the algorithm to efficiently navigate towards the target while avoiding obstacles, greatly improving the efficiency of path planning and the convergence speed of the algorithm. Bi-directional expansion strategies.

The Bi-RRT strategy, while capable of enhancing path search efficiency and reducing the number of iterations, still exhibits limitations in terms of the quality of initial solutions and the speed of convergence to the optimal solution. To address these issues, researchers have introduced the probabilistic smoothed Bi-RRT (PSBi-RRT) algorithm [17]. This algorithm integrates kinematic optimization, posture estimation, goal-oriented sampling, and node correction techniques to mitigate collision risks in complex environments. Additionally, it employs the θ-cut mechanism and triangular inequality-based node connections to further improve the accuracy and optimality of path planning.

Improvements in path nodes primarily involve the adoption of brute-force matching strategies and regression analysis. These methods utilize node backtracking strategies to reduce the probability of repetitive sampling, thereby effectively eliminating unnecessary nodes in the path [18]. Fig. 2 illustrates a two-wheeled mobile robot and its search strategy when dealing with depression traps. These enhancements have been validated in critical applications such as fire-fighting robots, providing crucial technological support for the efficient operation of autonomous mobile robots in challenging environments. These enhancements not only show the applicability of the RRT algorithm in complex environments but also highlight its potential in dynamic path planning and rapid response.

In order to improve the performance of RRT algorithm and its variants, many researchers have tried to improve it from different directions, and the main improvement strategies are shown in Fig. 3.

(a) (b) (c)

Fig. 2 (a) The two-wheeled firefighting robot; (b) when the Goal-bias RRT algorithm encounters the sag trap, there are more search nodes; (c) when the bidirectional RRT algorithm meets the depression trap, there are fewer search nodes

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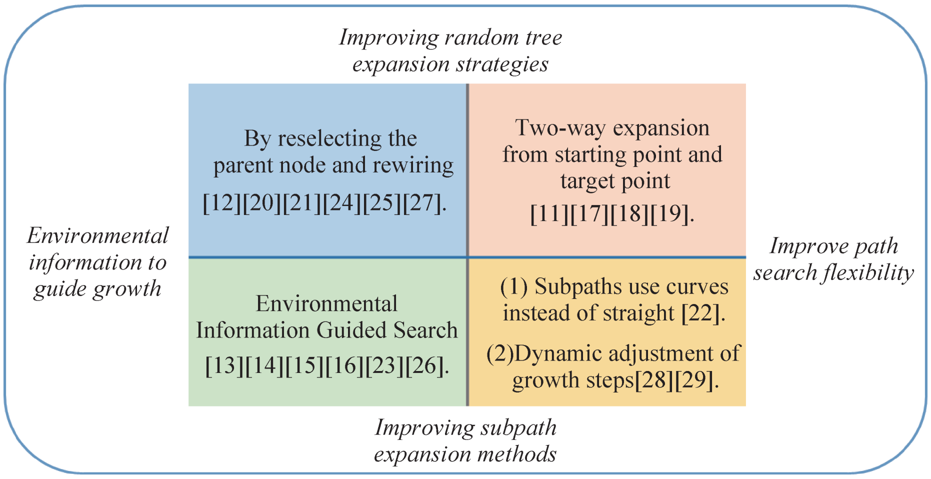

Fig. 3 RRT algorithm and its variant improvement strategies

RRT*, as a classical improvement method based on RRT, minimizes the cost of the current node and the initial node by reselecting the parent node and rewiring operation and reduces the randomness of the path search. The combination of greedy heuristic sampling with RRT-Connect further optimizes sampling efficiency and reduces redundant iterations, with the key to heuristic sampling being the determination of the expansion area. In this context, Ding et al. proposed the extended path RRT* (EP-RRT*) [19] based on path expansion area heuristic sampling. This approach involves rapidly exploring the environment to find a feasible path and then expanding it to determine the heuristic sampling area. Furthermore, since RRT* takes up a large amount of time and memory in the convergence process of multiple iterations, it leads to slow convergence and reduces the search efficiency. Therefore, scholars have improved it by limiting the sampling points to an elliptical range[20-21], using curves instead of straight paths to improve obstacle avoidance efficiency [22], using environmental feedback to correct deviations [23], and updating the starting point in real time [24-25], which can effectively improve the convergence speed of the algorithm. In the evolution of the RRT algorithm, the integration of algorithms and the application of dynamic step strategies have significantly enhanced its path planning performance in complex environments [26]. The incorporation of potential field functions into RRT, resulting in the development of the P-RRT algorithm [27], has markedly reduced the number of iterations and accelerated the convergence speed. Further advancements include the combination of P-RRT with Quick-RRT*, which not only speeds up the convergence process but also ensures the generation of optimal solutions [28]. For instance, the improved dynamic step RRT algorithm, utilizing the adjustable function AdutableSteer and its factor k, offers a new direction in path planning technology by enabling adjustable step lengths [29]. Combined with a novel path length control strategy, it effectively addresses path planning challenges in complex environments, particularly enhancing computational efficiency and path quality. Suitable for areas with intricate terrain and dynamic obstacles, this algorithm is crucial for applications in surveillance, search and rescue, and environmental monitoring. However, it requires further optimization in responsiveness and real-time data processing capabilities to meet the challenges of extremely dynamic or unpredictable environments.

(2) PRM algorithm

PRM algorithm is a planning algorithm that obtains paths by multiple queries based on the graph structure. The specific process of the algorithm mainly includes obtaining probabilistic road maps and searching for optimal paths from the probabilistic road maps. Firstly, a certain number of points are randomly collected in the map; the points falling on the obstacles are eliminated; all adjacent two points outside the obstacles are connected, and the line through the obstacles is removed to get the probabilistic roadmap; then a suitable search algorithm is used to search for the optimal path from the obtained probabilistic roadmap. The PRM algorithm has probabilistic completeness, which means that as long as the optimal path exists in the probabilistic roadmap, the optimal path can be found from it. However, the number and setting of sampled points during the search process will have a significant impact on path planning. Insufficient sampled points will result in the inability to plan a reasonable path in narrow spaces, while too many sampled points will increase the computational burden and reduce planning efficiency [30].

In the field of path planning, especially regarding the challenge of locating sampling points within narrow passages, a series of complementary innovative methods have been developed, collaboratively working to enhance sampling efficiency and overall path planning performance. For instance, by integrating global goal-oriented sampling with random sampling strategies [31], not only has the probability of effectively locating sampling points in narrow areas been increased, but also local nodes have been strengthened using Gaussian distribution, creating new connecting nodes in hard-to-reach areas. This approach not only enhances map connectivity but also effectively reduces the number of path nodes, thereby improving the efficiency of the overall planning process. Furthermore, optimizing the configuration of the sampling space [32] reduces the area generated by random nodes, lowering the generation of ineffective paths while maintaining a constant number of sampling points, thereby further enhancing sampling efficiency in narrow areas. Adjusting the connection distance between sampling points[33] reduces the time spent in the path search stage, making the entire path planning process more efficient. The combined application of these technologies not only addresses specific challenges in path planning but also demonstrates their importance and effectiveness in diverse application scenarios, collectively constructing a more efficient and precise path planning system.

1.1.2 Planning methods based on graph search

Path planning algorithms based on graph search construct a grid map based on a known environment, representing obstacles, starting points, and other information in the environment using grids. Each grid represents local environmental information, and free grids outside the obstacles are connected. A collision-free path is searched in the grid map through a search algorithm, as shown in Fig. 4. The paths obtained by graph search methods are often non-smooth and require further smoothing. Grid maps are a commonly used environmental modeling method in path planning and usually need to be combined with intelligent algorithms such as A* algorithm, D* algorithm, and Dijkstra algorithm.

(1) A* algorithm

The A* algorithm is a commonly used algorithm for pathfinding and graph traversal. It calculates the actual cost of node n to the starting point plus the estimated cost from node n to the target and chooses the node with

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the lowest cost as the next node to search until the lowest cost path is found. The estimated cost is typically calculated using the "Manhattan distance" or "Euclidean distance".

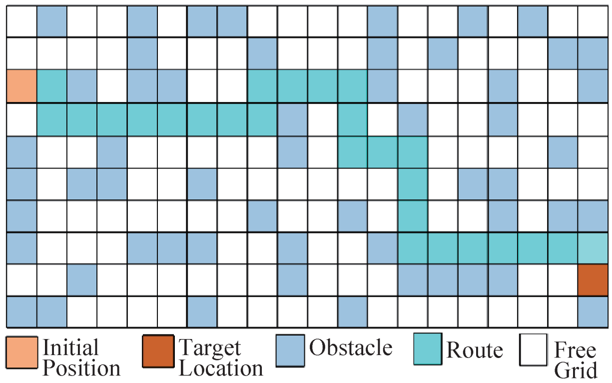

Fig. 4 Raster map

To address the limitations of the A* algorithm, such as excessive turning points, insufficient smoothness, and low adaptability in narrow spaces, researchers have proposed a series of optimization strategies [34]. These improvements focus primarily on enhancing path smoothness, safety mechanisms [35], and search efficiency. For instance, the introduction of path smoothing strategies and safety protection mechanisms eliminates redundant turning points and corner-cutting [36] and improves the path's smoothness and safety. Furthermore, some studies have employed reverse search strategies [37] and dynamic circular smoothing to reduce invalid points [38] and increase overall path planning efficiency.

In addition, enhancing the heuristic function is an important way to improve the A* algorithm. The heuristic function in the A* algorithm is enhanced by adding cosine coefficients to the Euclidean distance model, $L'(n)$ as shown in Eq. (3), and the new cost estimation heuristic function employs $\cos\theta$ to measure the consistency between the search direction and the direction of the target point. As the value of $\cos\theta$ is closer to 1, the angle between these two directions is smaller, indicating that it is closer to the target point [39].

$$L'(n) = \begin{bmatrix} M_0 - M_1 \end{bmatrix} \begin{bmatrix} L(n) \\ \cos\theta \end{bmatrix} \tag{1}$$

where $L(n)$ denotes the Euclidean distance between the current position and the target position; $[M_0 - M_1]$ represents the straight-line distance between two points.

The computation of the cosine value is as follows: It is assumed that there is a vector triangle path formed by points $A(x_1, y_1)$, $B(x_2, y_2)$, and $C(x_3, y_3)$, as shown in Fig. 5.

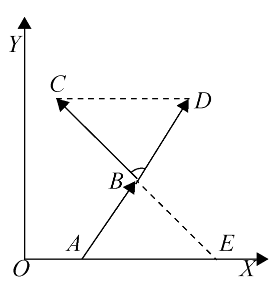

Fig. 5 Vector triangle path

From the diagram, it can be deduced that $\triangle ABE \sim \triangle DBC$.

$$\begin{cases} AB = BD = (x_2 - x_1)i + (y_2 - y_1)j \\ BC = (x_3 - x_2)i + (y_3 - y_2)j \end{cases} \tag{2}$$

$$\cos\theta = \frac{BD \cdot BC}{|BD||BC|} = \frac{\left(x_3 - x_2\right)\left(x_2 - x_1\right) + \left(y_3 - y_2\right)\left(y_2 - y_1\right)}{\sqrt{\left(x_2 - x_1\right)^2 + \left(y_2 - y_1\right)^2}\sqrt{\left(x_3 - x_2\right)^2 + \left(y_3 - y_2\right)^2}} \tag{3}$$

(2) D* Algorithm

Unlike A* algorithm, D* algorithm is a dynamic heuristic path search algorithm that performs a reverse path search from the target position to the starting position. The entire planning process mainly includes two steps: static path planning and dynamic search. Compared with A* algorithm, the biggest advantage of D* algorithm is that it does not require obtaining map information in advance and can still ensure that the robot continuously optimizes the path by quickly exploring complex environments with dynamic obstacles.

However, the D* algorithm does not address the issue of non-smooth paths caused by excessive turning points. Currently, improvements based on the D* algorithm mainly focus on reducing turning points, increasing path smoothness, and improving path search efficiency. For example, innovative node selection methods enable the algorithm to precisely identify key nodes in complex maps, reducing redundancy and potential risk points in the path while enhancing the algorithm's adaptability to narrow and intricate areas [40-41]. The incorporation of obstacle constraints in the cost function and B-spline smoothing techniques further improves the smoothness of the path [42-43]. The application of these techniques not only enhances path safety but also significantly improves the continuity and fluidity of the path. Moreover, to enhance the efficiency and quality of path searching, smoothness functions based on Euclidean metrics optimize the search space and narrow the range of single-node searches, effectively improving the accuracy and efficiency of the search [44]. This holistic approach to improvement makes the D* algorithm more efficient and precise in handling path planning in complex environments, especially in scenarios requiring consideration of multiple constraints and variables, demonstrating its remarkable adaptability and flexibility.

(3) Dijkstra algorithm

In the field of computational graph theory, enhancing the Dijkstra algorithm has been a focal point of recent research, primarily aimed at addressing its inherent limitations in efficiency and adaptability for complex network applications. A significant advancement in this area is the integration of a bidirectional search strategy[45], which revolutionizes the traditional unidirectional search approach. This strategy, initiating searches simultaneously from both the source and destination, significantly reduces computational iterations, thereby improving the overall efficiency of the path-finding process.

The strategy of dynamically updating weighted path results into a database system, coupled with time window-based path scheduling and replanning [46], not only simplifies the computational process but also enhances the overall system efficiency, particularly in scenarios involving fluctuating network conditions and priorities. Moreover, the introduction of the octile search algorithm [47] marks a substantial step forward in improving path smoothness, effectively reducing the angularity of turns in computed paths, resulting in more

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streamlined and efficient routes. A paradigmatic shift in optimization objectives has been widely adopted, moving from traditional path length weighting to time-based weighting [48]. This shift towards temporal efficiency reflects a deeper understanding of practical navigational needs in complex networks, leading to more effective and contextually relevant path solutions. Additionally, the incorporation of pheromone concepts from ant colony algorithms into the Dijkstra framework [49] has significantly reduced path redundancies, enhancing the algorithm' s ability to discern more efficient routes through dense network graphs. The application of estimation functions for rapidly determining the shortest paths [50] plays a crucial role in significantly enhancing computational efficiency. This heuristic-based approach accelerates the path-finding process, enabling quicker responses in dynamic network environments and making the Dijkstra algorithm more robust and versatile for contemporary path planning challenges.

1.1.3 Intelligent bionic global path planning method

The application of intelligent bionic methods in path planning mainly imitates the behavior of biological populations or ecological mechanisms for computation, which is highly flexible, able to respond to changes in the environment, parameters, and tasks in real time and able to optimize the path through continuous self-learning to improve the adaptive ability of the algorithm. Therefore, it has been widely used in mobile robot trajectory planning. At present, the commonly used algorithms are genetic algorithm (GA), ant colony optimization (ACO), particle swarm optimization (PSO), and so on.

(1) Genetic algorithm

GAs are innovative examples of global optimization search algorithms that draw inspiration from the principles of natural selection and genetic mechanisms. By simulating the evolutionary process and exploring the solution space on a population basis, each individual in the population represents a potential solution. Through an iterative process of selection, crossover, and mutation, the GA can efficiently converge to a population that is best adapted to the environment, approximating the global optimal solution, with excellent parallel performance and robustness and is a versatile tool for addressing various optimization challenges.

Recent advances in GAs highlight their continued evolution in addressing the complexity of modern optimization problems. These algorithms have demonstrated their versatility and long-term applicability in the field of computational optimization by incorporating adaptive strategies and domain-specific enhancements. Nonetheless, GA still faces challenges when dealing with complex multidimensional problems, especially when the population size is small, which may lead to slower convergence in the later stages of the search process. To overcome these limitations, researchers have employed adaptive methods to improve the efficiency and effectiveness of genetic algorithms. In particular, adaptive crossover and mutation probabilities are crucial for solving complex nonlinear problem spaces by maintaining the diversity of the algorithms while being able to efficiently guide the algorithms to converge to the optimal solution [51].

Within the framework of genetic algorithms, domain knowledge-based operators [52] represent a more targeted and problem-specific adaptation. This tuning allows genetic algorithms to utilize the characteristics of a specific problem domain, thus improving problem solving capabilities. In computational optimization, strategic tuning of the direction and magnitude of the variation vectors [53] is a key step in refining the search algorithm.

This tuning helps the GPS to balance the need for exploration and exploitation in a multidimensional solution space, effectively pointing to the most promising solutions while improving the speed of convergence and the quality of the solutions. The development of complex crossover operators [54] is another significant advancement that enhances the reorganization mechanism of GA. These advances help to combine the features of the parents more efficiently, produce offspring that can better adapt to the problem domain, speed up the convergence rate, and increase the likelihood of finding excellent solutions. Combining suboptimal entities from the ACO algorithm [55] with migration and optimization operators brings richness to the evolutionary framework of genetic algorithms. This integration improves the quality of the initial population and provides a more diverse and robust basis for the search [56]. The introduction of migration and optimization operators pushes the dynamic search paradigm, accelerates the convergence process, and enables efficient navigation in complex solution spaces. Furthermore, the implementation of multi-domain inversion strategies [57] emphasizes the importance of enhancing the local search capabilities of genetic algorithms.

(2) Ant colony optimization

The ACO algorithm is inspired by the foraging behavior of ants, and it solves the optimization problem by modeling the pheromone trajectories left by ants. In this model, each ant represents a potential solution and will choose its path based on the pheromone concentration. A higher pheromone concentration on the path indicates that the path is more efficient, thus allowing the ant colony to get closer to the optimal solution during the iteration process.

In the latest research on ACO optimization, improving the pheromone distribution and updating mechanism are considered to be the key to improving the efficiency of the algorithm and the convergence speed. Instead of the traditional uniformly distributed approach, researchers now prefer a non-uniform pheromone distribution method with strategically adjusted pheromone concentrations after each iteration. This approach helps reduce aimless blind search and focuses the algorithm’s search process on paths that are more likely to find optimal solutions. In addition, the use of different pheromone updating strategies and the combination of local search optimization techniques have been shown to significantly improve the probability of identifying optimal paths [58]. For example, Wu et al. introduced a heuristic mechanism equipped with directional information, as shown in Fig. 6, which reduces computational complexity by minimizing redundancy in the search process [59]. They also improved the heuristic function, as shown in Eq. (6), to effectively avoid blind searching, thereby increasing the algorithm’s search efficiency and adaptability.

The diagram illustrates the reduction of eight possible points (P_1, P_2, $\cdots$, P_8) at the current location to three selectable points (P_1, P_2, P_3), based on heuristic information. This process is further enhanced by a heuristic function to increase the search objective and path smoothness, with the improved heuristic function formula presented.

$$\eta(i,j)' = \frac{1}{g \cdot d_{\mathrm{S}j} + h \cdot d_{j\mathrm{T}} + a \cdot c(i)} \tag{4}$$

where $\eta(i,j)'$ represents the improved heuristic function; $d_{\mathrm{S}j}$ is the distance from the starting point to the next point, and $d_{j\mathrm{T}}$ is the distance from the next point to the target point; g is the weight of $d_{\mathrm{S}j}$, and h is the weight of

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d_{jT}, where g and h satisfy $g+h=1$; $c(i)$ represents the number of turns from the previous point $i-1$ to the next point j ; a is the turning coefficient.

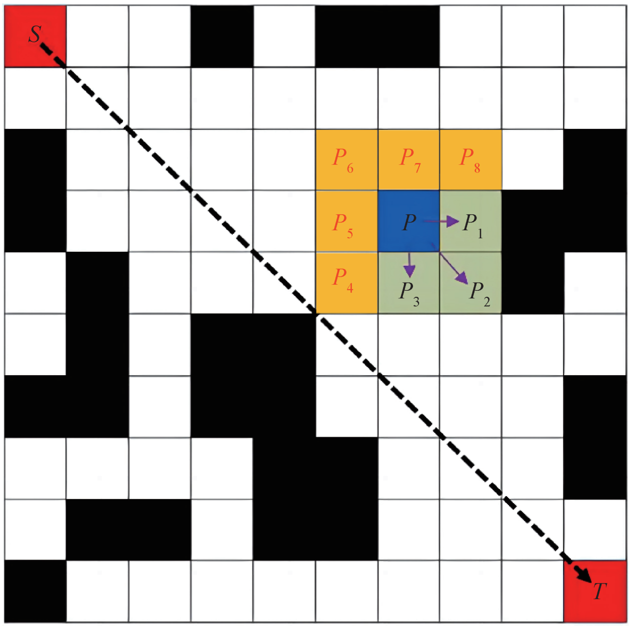

Fig. 6 Heuristic mechanism based on orientation information

In the performance evaluation of ACO algorithms, convergence speed is a key index, which is largely influenced by the pheromone update strategy [60]. Recent studies have shown that by adding adaptive factors to the pheromone evaporation process and heuristic information, the convergence speed can be effectively balanced with the global search capability [61], which not only reduces the redundancy in the search process but also accelerates the convergence speed, which in turn improves the overall search efficiency [62]. In addition, enhancing internal communication among ant colonies and fully utilizing historical search data have been shown to significantly improve the convergence speed and search efficiency of the algorithm [63]. The introduction of a penalty mechanism in the pheromone updating strategy can steer the search process away from less efficient paths [64], thus reducing the repeated exploration of suboptimal paths and increasing the exploration of unknown regions [65]. Through the application of these methods, the ACO algorithm can find the optimal solution more efficiently while reducing unnecessary computation and resource consumption.

(3) Particle swarm optimization

PSO is a search optimization algorithm inspired by the foraging behavior of birds, which simulates the cooperative and information-sharing behaviors of birds during foraging to find solutions. In PSO, each particle represents a potential solution, and the whole system consists of numerous particles. At each iteration, particles update their positions and velocities based on their own historical best records, as well as the global best solution of the whole flock, thus searching for the optimal solution in the solution space.

Although PSO performs well in terms of global search and convergence speed, it may fall into the problem of local optimal solutions when dealing with high dimensional and complex problems. To address this challenge, researchers have focused on improving the search mechanism and updating strategies to enhance the algorithm’s exploration capabilities and reduce the risk of falling into local optimal solutions. These improvements mainly focus on increasing the diversity and independence between particles. For example, the introduction of a jumping mechanism allows particles with lower mass to escape from the local optimum, thus facilitating broader exploration [66]. In addition, adaptive tuning based on the fitness evaluation function not only deepens the exploration of the solution space [67] but also achieves a balance between global search and local refinement.

Moreover, introducing an adaptive fractional order velocity is a significant advancement in the algorithm. Unlike the fixed parameter settings in traditional PSO, this improvement employs an adaptive mechanism that allows algorithm parameters to dynamically adjust according to the evolutionary state of the particle swarm. By utilizing the real-time evolutionary characteristics of the group, it introduces varying perturbations [68]. The updates of velocity and position as shown in Eqs. (5) and (6) effectively prevent the particle swarm from falling into local optima, thus enabling a more extensive exploration of the search space.

$$v_i^{k+1} = \alpha v_i^k + \frac{1}{2}\alpha(1-\alpha)v_i^{k-1} + \frac{1}{6}\alpha(1-\alpha)(2-\alpha)v_i^{k-2} + \frac{1}{24}\alpha(1-\alpha)(2-\alpha)(3-\alpha)v_i^{k-3} + c_1 r_1 (x_{ib}^k - x_i^k) + c_2 r_2 (x_{gb}^k - x_i^k) \tag{5}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{6}$$

$$c_1 = (c_{1i} - c_{1f})\frac{k_{max} - k}{k_{max}} + c_{1f} \tag{7}$$

$$c_2 = (c_{2i} - c_{2f})\frac{k_{max} - k}{k_{max}} + c_{2f} \tag{8}$$

$$\alpha = 0.9 - \frac{1}{1 + e^{-E_f^k}}\frac{k}{k_{max}} \tag{9}$$

$$E_f^k = \frac{d_{gb}^k - d_{min}^k}{d_{max}^k - d_{min}^k} \tag{10}$$

where $c_{1i}(c_{2i})$ and $c_{1f}(c_{2f})$ denote the initial and final values of the acceleration coefficients c_1 and c_2, respectively; k_{max} is the maximum number of iterations; α denotes the fractional-order speed of linear adaptive adjustment according to the evolutionary state of the swarm; E_f^k denotes the evolutionary factor that can reflect the evolutionary state of the swarm at the kth iteration; d_{max}^k and d_{min}^k denote the maximum and minimum values of the mean distances from one particle in the swarm to the other particles; d_{gb}^k denotes the average distance of gbest.

Additionally, by designing customized PSO strategies for different problem types, the applicability and effectiveness of the algorithms have been significantly improved, and the method of integrating other algorithms is one of the key strategies for extending the scope of PSO applications. For example, combining PSO with the simulated annealing algorithm introduces a new particle update mechanism that effectively prevents the algorithm from prematurely converging to a local optimum solution [69]; combining PSO with the APF algorithm enhances the specific functionality for solving certain obstacle avoidance problems [70]; the proportional-integral-differential (PID)-based PSO strategy, known as PBS-PSO that aims at accelerating the convergence process, redirecting the search and avoiding the emergence of local optimal solutions [71]. These improvements to the PSO

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algorithm not only address its limitations in specific application scenarios but also extend its potential applications in a wide range of optimization problems

1.2 Local obstacle avoidance algorithm

Local obstacle avoidance algorithms focus on navigating a mobile robot in its immediate surroundings, ensuring that it can safely and efficiently circumvent obstacles while moving towards its target. Several strategies and techniques are used for local obstacle avoidance, and these methods can be crucial in enhancing the performance of mobile robots. Here are some notable local obstacle avoidance algorithms

1.2.1 Dynamic window approach

The dynamic window approach (DWA) is a real-time path planning method that accounts for the dynamic constraints of mobile robots. The essence of the algorithm lies in sampling within the velocity space (v, w) and simulating motion trajectories, combined with an evaluation function to select the optimal path. This involves precise control of the robot's velocities, including both linear and angular speeds. A significant challenge in the practical application of DWA is efficiently exploring the velocity space to find the optimal solution while avoiding local optima [72].

A crucial aspect of improving the algorithm is optimizing the sampling strategy in the velocity space. Incorporating the minimum turning radius not only ensures the feasibility of the trajectory but also enhances the practical applicability of motion planning [73]. Utilizing deep reinforcement learning to adjust a robot's linear and angular velocities allows for more flexible trajectory adjustments during obstacle avoidance. This approach has achieved significant results in improving obstacle avoidance efficiency in dynamic and unpredictable environments, resulting in a 23.7% increase in obstacle avoidance rate [74]. Another approach to counter the tendency of the DWA algorithm to fall into local optima is the dynamic selection of parent nodes. By dynamically incorporating the target into the parent node selection, the algorithm more effectively avoids falling into local optima post-obstacle avoidance [75]. Moreover, constructing sub-goals online based on the principle of minimal path cost addresses the issue of sub-optimal sub-goal points while enhancing the overall efficiency and accuracy of path planning [76]. Optimizing the evaluation function is the key to enhancing the efficiency and accuracy of path planning. Introducing new evaluation metrics and adjusting weight coefficients are tailored to meet the practical demands and environmental characteristics of path planning. Including the distance from the current position to the target point as an evaluation metric aids in the direct quantification of proximity to the goal, especially useful in complex obstacle environments, thereby allowing for more accurate path adjustments [77]. Furthermore, incorporating the decay coefficient of the predictive function and global yaw angle helps maintain a global optimum orientation over long-duration movements, preventing deviation from the optimal path due to local obstacle configurations [78].

In specific application scenarios, the introduction of forward guidance direction as an evaluation metric plays a crucial role in ensuring stability and safety, which can greatly improve the obstacle avoidance rate and safety in complex environments [79]. In view of the uncertainty and variability of environments, the introduction of a fuzzy controller to adjust the adaptability of the evaluation function's weight coefficients is vital, allowing the algorithm to flexibly adjust to real-time environmental changes [80]. In dynamic or unpredictable environments, adaptively adjusting the objective function's weight to balance speed and safety enables rapid and secure navigation in complex settings [81]. This is particularly important for real-world engineering applications such as autonomous vehicles, industrial robots, and emergency response systems. While the algorithm excels in environments with dense obstacles, it still has certain limitations in handling environmental complexity and rapid changes, necessitating further optimization and real-world application testing.

In the trend of artificial intelligence development, the integration of deep learning into algorithms is garnering increasing attention. This approach, by mimicking human behavior, not only improves obstacle avoidance quality but also optimizes the entire navigation process. For instance, in complex environments such as shopping malls or airports, deep learning enables robots to serve people more effectively, demonstrating enhanced capabilities in navigation and interaction [82] as shown in Fig. 7.

Fig. 7 Mobile robots for airport navigation

By redefining the state space, action space, and reward function of the DWA algorithm and utilizing Q-learning to adaptively learn the parameters of DWA, as demonstrated in Eq. (11), the algorithm's convergence speed is optimized. This enhancement significantly improves its navigation efficiency in unknown environments [83].

$$Q(s,a) = (1-\delta)Q(s,a) + \delta[R(s,a)+\gamma Q(\tilde{s},\tilde{a})] \tag{11}$$

where $\delta \in (0,1)$ is the learning rate; $\gamma \in (0,1)$ is the discount factor. A larger γ value indicates a greater inclination towards long-term value, while a smaller γ value shows a focus on immediate benefits; $R(s, a)$ represents the reward obtained from the environment for the current state and action; $Q(\tilde{s},\tilde{a})$ is the maximum Q value among all actions corresponding to the next state.

These improvements not only enhance the real-time performance and adaptability of the algorithm but also open new avenues and perspectives for future development. Despite their theoretical superiority, the ability to adjust a robot's linear and angular velocities to adapt to dynamic environments and improve obstacle avoidance efficiency may involve high costs and require extensive training data. Consequently, this could limit their widespread application and efficiency in practical scenarios. Moreover, although the Q-learning algorithm excels in improving the algorithm's convergence speed, it may still face limitations in adaptability and robustness in unknown environments. While the integration of advanced artificial intelligence technologies can

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significantly enhance algorithmic performance, cost-effectiveness and applicability across various scenarios must also be considered in real-world applications. Fig. 8 shows the different improvement strategies of the DWA algorithm.

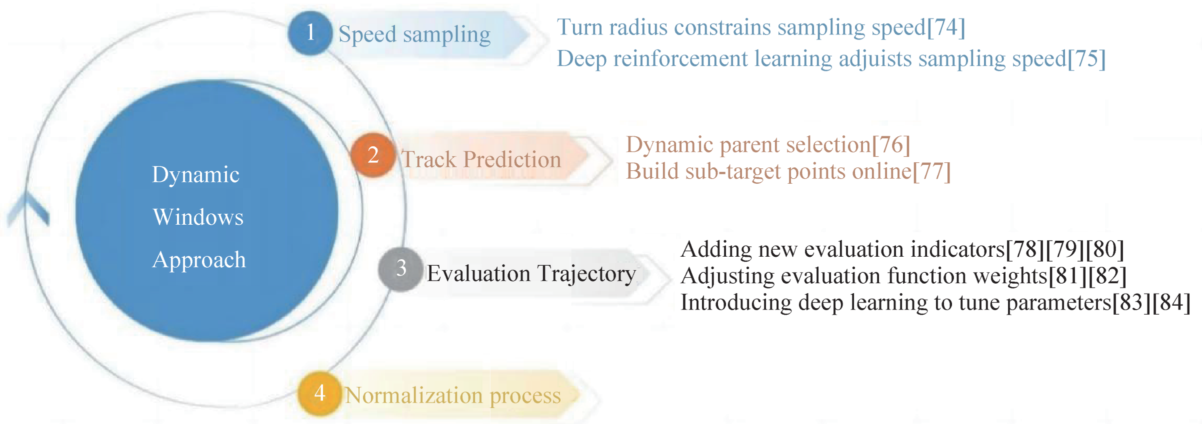


Fig. 8 Different improvement strategies for DWA algorithm

1.2.2 Artificial potential field

APF algorithm is a path planning method based on the principles of physical force fields. By setting attractive potential fields at the target location and repulsive potential fields at obstacles, mobile robots experience an “attraction” towards the target and a “repulsion” from obstacles. This attraction propels the robot towards the target, while the repulsion steers it away from obstacles. However, a significant challenge of this algorithm is its propensity to fall into local minima, leading to reduced efficiency in path planning.

In self-driving cars, the APF algorithm must respond in real-time to changing road and traffic conditions. However, its local minima issue could lead to decreased driving efficiency or inaccuracies in complex traffic scenarios. Many researchers have focused on the design and parameter adjustment of the potential field function, adopting various strategies to enhance the obstacle avoidance efficiency and path planning quality of the APF algorithm. A notable approach in algorithmic structural optimization includes the use of a deterministic annealing strategy [84], which involves the introduction of a temperature parameter to refine the potential field function, thereby enhancing the robot’s flexibility in complex environments and reducing the risk of falling into local minima. Additionally, geometric methods, such as redefining the potential field function and employing equipotential line tangent circles for precise obstacle management [85], have significantly improved the efficiency and accuracy of path planning.

With the advancement of research, the integration of various algorithms has been effective in enhancing obstacle avoidance efficiency and adaptability, avoiding potential local minima issues. For instance, a dense learning algorithm is utilized to predict the obstacle state space by combining long short-term memory (LSTM) recurrent neural networks and Q-learning . Simultaneously, adjusting the detection radius of the virtual potential fields enables the unmanned vehicle to successfully navigate around dynamic obstacles[86]. The LSTM Q-Learning structure is shown in Fig. 9.

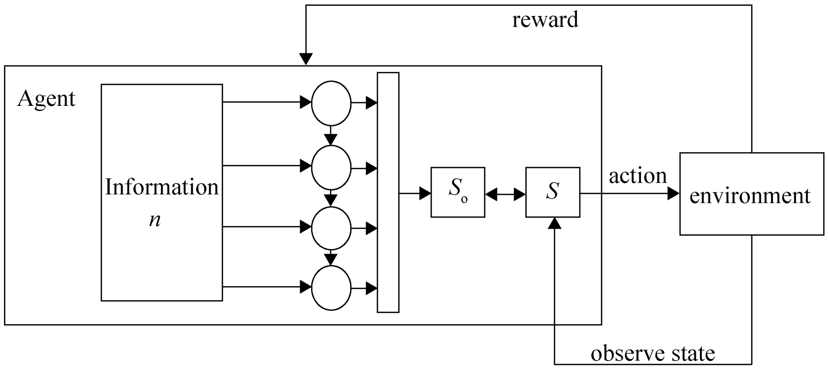


Fig. 9 LSTM Q-Learning structure

$$d_{\mathrm{O}k}=\sqrt{r^2-\frac{d_{a_1a_2}^2}{2}}+\sqrt{R^2-\frac{d_{a_1a_2}^2}{2}} \tag{12}$$

where $d_{\mathrm{O}k}$ represents the distance between the obstacle and the unmanned vehicle; r is the radius of the obstacle's repulsive field; R is the radius of the circular model of the virtual potential field, and $d_{a_1a_2}$ is the distance at which the two circles intersect.

$$reword=\begin{cases}-1, & d_{\mathrm{O}k}\leqslant v\cdot\Delta t+d_{\mathrm{safe}}\\ 1, & d_{\mathrm{O}k}>v\cdot\Delta t+d_{\mathrm{safe}}\end{cases} \tag{13}$$

where $v{\cdot}\Delta t$ denotes the distance the car travels at its current speed. When the distance between the unmanned vehicle and the center of the obstacle is greater than the predicted distance of the vehicle, a positive reward is given, indicating a safe distance. Otherwise, it represents a collision, thereby changing the direction of the unmanned vehicle away from the predicted area.

Furthermore, the incorporation of posture threshold gain and simulated annealing optimization algorithm in the potential field function model [87] further overcomes linear interference, augmenting the stability and reliability of the algorithm. The use of dynamically enhanced algorithms, such as a fireworks algorithm based on the Euclidean distance, provides a more flexible adjustment mechanism for the APF algorithm, effectively enabling it to "escape" from local minima [88].

With the continuous advancement of reinforcement learning, incorporating reinforcement learning algorithms into the APF algorithm has become an effective way to improve the overall performance of the APF algorithm [89-91]. By learning from environmental information and historical data, the adaptability of the APF algorithm to the environment can be effectively enhanced, while good convergence speed and stability can be maintained. The future of technological development will focus on enhancing the performance and adaptability of the APF algorithm, especially in dynamic and complex environments. With the advancement of machine learning and artificial intelligence technologies, more research is expected to concentrate on integrating these advanced technologies with the APF algorithm. This integration aims to improve the accuracy of obstacle detection and the efficiency of path planning. Technologies like deep learning, particularly convolutional neural networks (CNN) and LSTM networks, will provide the algorithm with a deeper understanding and prediction capabilities of the environment, thereby optimizing real-time decision-making processes. Additionally, the development of new potential field functions and the incorporation of more complex computational models will be key research directions. These advancements are geared towards enabling the algorithm to better adapt to various environmental conditions and challenges.

1.2.3 Time elastic band

The time elastic band (TEB) algorithm represents an advanced method in robotic path planning, aimed at comprehensively considering dynamic constraints to achieve multi-objective optimization. Unlike traditional Elastic Band algorithms, the TEB algorithm modifies the initial trajectory generated by the global planner and defines the motion time between path points, transforming the path planning problem into a multi-dimensional optimization issue [92]. The sparsity of the system matrix, due to the robot's state at discrete time points, becomes the key to optimization. Utilizing efficient frameworks like "g2o", the TEB algorithm manages dynamic obstacles and motion constraints while maintaining high efficiency and robustness [93].

Enhancing safety in path planning has become a key direction in current research. Researchers have enhanced the safety of robots in complex environments by introducing hazard penalties and acceleration adjustments. The application of endpoint smoothing constraints has improved the continuity of path planning, allowing robots to adjust their trajectories more smoothly [94]. The integration of nonlinear model predictive control permits more precise handling of motion planning in non-Euclidean spaces. By utilizing nonlinear operator techniques to manage rotational components across non-Euclidean rotation groups, it enhances the efficiency of motion planning overall, as well as in generic and cross-scenario complex spaces [95]. By integrating the strengths of the TEB technique and the hybrid reciprocal velocity obstacle (HRVO) model, potential collisions generated by the HRVO model are incorporated into the objective function of the TEB technique [96]. This allows mobile robots to navigate safely in dynamic social environments. This is particularly applicable to robotic systems operating in dynamic and unpredictable environments, such as autonomous vehicles, industrial robots, and drone navigation, addressing key challenges like obstacle avoidance, efficient path planning, and minimizing collision risks in complex settings. Moreover, for scenarios involving following moving targets or navigating in crowds, the addition of dynamic pedestrian cost maps [97] optimizes local path planning while ensuring safety, enhancing the algorithm's applicability in densely populated settings, as shown in Figs. 10 and 11.

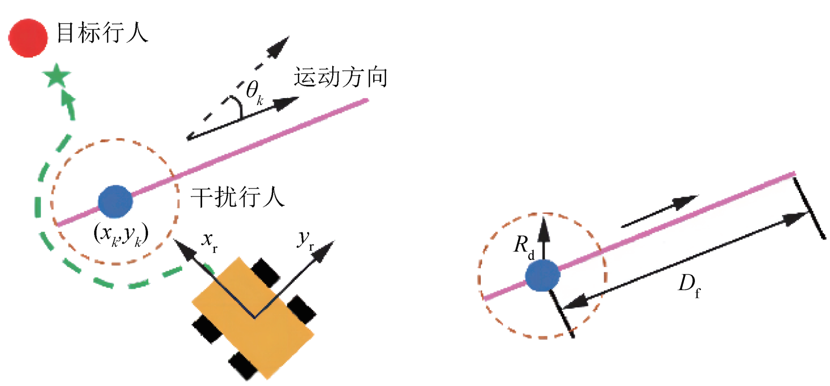
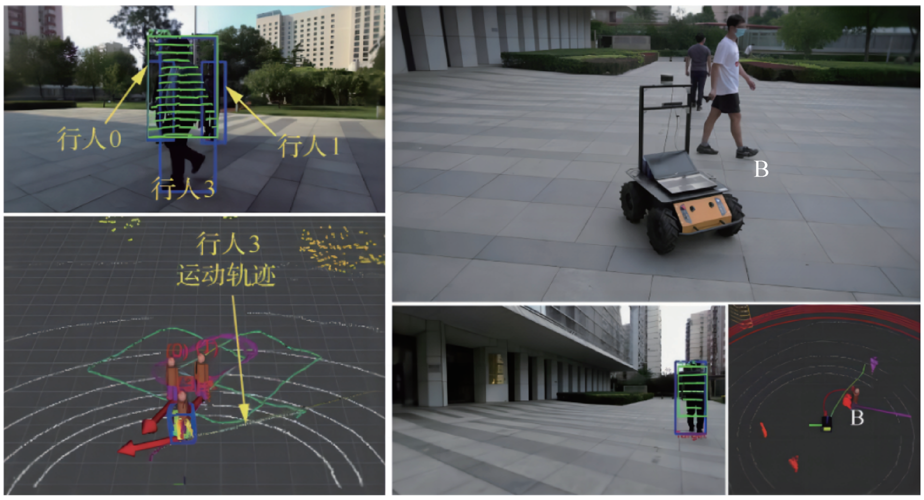


Fig. 10 Robot movement route and pedestrian cost map

where (x_k, y_k) represents the coordinates of the pedestrian; θ_k represents the direction of pedestrian movement, and D_f represents the length of the virtual obstacle. The calculation formula is as follows:

$$D_f = \rho v = \rho \sqrt{\dot{x}_k^2 + \dot{y}_k^2} \tag{14}$$

where ρ is the velocity coefficient; v is the pedestrian velocity, and $(\dot{x}_k, \dot{y}_k)$ are the velocity components of the pedestrian coordinates relative to the x_r and y_r axes of the robot coordinate system.



(a) (b)

Fig. 11 (a) Motion state estimation; (b) obstacle avoidance effect demonstration

The introduction of minimum distance constraints [98] also prevents unnecessary detours by robots in complex environments, further enhancing the quality of the path. In the further development of the TEB algorithm, optimizing the smoothness and efficiency of path planning has become a focal point. Particularly in handling path turns or changes, the incorporation of acceleration constraints [99] significantly improves the continuity and smoothness of the path, thus enhancing the stability and operability of robots in complex environments. At the same time, a new multi-objective local path topology optimization method has been proposed, specifically adapting to scenarios requiring real-time path planning in resource-limited settings through precise path and speed strategies [100].

Despite these improvements, the TEB algorithm still faces limitations in high-dimensional and complex environments, indicating a need for future research to further explore the algorithm's adaptability and robustness [101]. In view of the limitations of the TEB algorithm in high-dimensional and complex environments, future research might involve integrating deep learning and other advanced algorithms to enhance the adaptability of the TEB algorithm in these challenging settings. The local obstacle avoidance algorithms play a crucial role in ensuring that mobile robots can navigate safely and effectively in real-world dynamic environments. Their capability to efficiently handle dynamic obstacles and adhere to motion constraints is essential for the autonomous movement of robots.

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2 Conclusion

While substantial advancements have been achieved in the domain of global path planning algorithms, disparities in performance and practical applicability persist. For instance, in sampling-based search algorithms, heuristic search techniques are incorporated to guide the expansion direction of the random tree, averting aimless search, thereby minimizing redundant nodes and boosting convergence speed. Bi-directional growth and dynamic step sizing are utilized to augment path planning efficiency. In the case of graph-based algorithms, the absence of reference information during the search often results in trajectories lacking in smoothness. To address this, numerous scholars have refined node expansion to curtail iteration counts, thereby reducing turn points and enhancing path smoothness. Intelligent biomimetic algorithms, with their high flexibility and adaptability, can persistently learn and rectify deviations in the path planning process to optimize the trajectory. To amplify the convergence speed and avert local optima entrapment, iterative updating techniques are typically refined for these algorithms.

Moreover, local obstacle avoidance algorithms, despite having lower computational demands than their global planning counterparts, mandate higher real-time performance and fine-tuned algorithm parameters. For instance, the DWA algorithm relies on the mobile robot’s real-time motion state to enhance the evaluation function and boost the overall path planning performance. The APF algorithm necessitates a meticulously designed potential field function that accurately depicts the repulsive and attractive forces of obstacles and target objects. The TEB algorithm needs to account for the mobile robot’s varying motion states and adjust parameters in accordance with environmental data.

In the process of mobile robot path planning, different algorithms can be fused to quickly, accurately, and stably plan paths based on actual needs and algorithm characteristics. Table 1 shows the advantages, disadvantages, and improvement principles of different algorithms.

3 Mobile robot obstacle avoidance movement trends

3.1 Improving and optimizing existing algorithms

Single algorithms, constrained by their inherent structures, often find application in specific scenarios and encounter challenges when tasked with rapidly devising high-quality paths within intricate environments. Consequently, augmenting the path planning process with relevant constraints becomes imperative. These constraints serve to surmount algorithmic limitations, thereby fostering enhancements in planning efficiency, convergence speed, and the quality of the resulting optimal solutions. Moreover, it is noteworthy that conventional algorithms exhibit limited transfer learning capabilities, heralding the emergence of a notable paradigm shift toward the amalgamation of deep learning, reinforcement learning, and meta-learning principles into algorithms, a progressive trajectory that is poised to shape the future of the field.

However, it is important to note that while the integration of deep learning, reinforcement learning, and meta-learning principles into algorithms represents progress, these technologies still face several challenges. First, such integration increases the complexity of the algorithms, necessitating more computational resources and data for effective model training. Second, deep learning models typically require a large amount of labeled data, which may be difficult to obtain in practical applications. The generalizability and interpretability of these models remain unresolved issues, potentially limiting their application scope in complex environments.

Table 1 Principle of improvement of different algorithms and their advantages and disadvantages

Path planning methods	Representative methods		Improvement principle	Advantages	Limitations
Global path planning methods	Sampling-based approach	PRM RRT	Heuristic search; dynamic adjustment of step size	Simple process; quick search	Blind search; stuck in a dead zone
	Graph-based search methods	A* D* Dijkstra	Reduce the number of iterations and inflection points	Rich environmental expression	High environmental model accuracy requirements
	Intelligent bionic approach	GA ACO PSO	Optimize individuals; improved individual interaction	Highly adaptable; highly efficient	Easily trapped in local optima; slow convergence in later stages
Local obstacle avoidance algorithm	DWA		Optimized evaluation function	Low computational complexity; high operability	High demand on the evaluation function; prone to local optima
	APF		Refining the potential field function	Highly real time	Require reasonable potential field functions
	TEB		Adding constraints	Multi-objective optimization	Strict parameter requirements

3.2 Combining the advantages of different algorithms

Diverse path planning algorithms bring with them unique strengths and weaknesses. As the environmental complexity escalates, the deployment of a single algorithm proves insufficient to grapple with an array of unforeseen scenarios. Consequently, a strategic recourse involves the selective integration of divergent algorithmic paradigms, tailored to the environmental and task-specific requisites. Through this judicious amalgamation, the distinct attributes of each algorithm synergize, optimizing the collective capabilities to their fullest extent. An illustrative example lies in the fusion of the PSO algorithm with the APF approach. This hybridization not only reduces path cost but also assures the expeditious traversal of densely populated obstacle-laden terrains by the mobile robot.

Although strategically combining different algorithms can significantly enhance path planning effectiveness, it also introduces a series of challenges. Effectively integrating diverse algorithms necessitates an in-depth understanding and precise adjustments, which not only increases the complexity of implementation but may also raise costs. Additionally, there could be conflicts or incompatibilities between algorithms under certain conditions, posing risks to system stability. Moreover, this approach of algorithm combination might make the system more sensitive to certain types of errors, thereby impacting its overall robustness.

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3.3 Improving the accuracy and authenticity of environmental maps

The foundation of path planning algorithms hinges upon the quality and precision of environmental information. Given this, the acquisition of precise environmental data assumes paramount importance. Mobile robots can leverage an assortment of sensory inputs, including visual cameras, LiDAR, and GPS systems, to obtain accurate environmental data and ascertain their own spatial orientation. Streamlining environmental data preprocessing and curbing data redundancy holds the key to the creation of increasingly accurate and authentic maps, elevating the quality of path planning to new heights.

While the integration of multiple sensor fusion technologies can enhance the accuracy and authenticity of environmental data, it also brings about its own set of challenges. For example, sensory systems may not fully adapt to environmental changes, such as in adverse weather conditions or complex terrains. High-precision sensory equipment often comes at a considerable cost, potentially increasing the overall investment in the system. Another important consideration is the need for high-performance computing resources when large volumes of environmental data are processed, which could limit the system’s flexibility and efficiency in practical applications.

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