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A Survey of Path Planning Algorithms for Inspection Robots

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ABSTRACT

Against the backdrop of inspection robots being widely applied in complex dynamic scenarios such as industrial automation and intelligent services, this paper systematically reviews three mainstream path planning algorithms—traditional algorithms (A*, Dijkstra, and their improved variants), sampling-based algorithms (PRM, RRT*, and their variants), and intelligent optimization algorithms (genetic algorithm, particle swarm optimization, ant colony optimization, and their enhancements)—by synthesizing domestic and international research. It examines their core principles, advantages, limitations, and applicable scenarios, with a focus on cutting-edge trends such as algorithm integration, multi-sensor perception synergy, and multi-objective optimization. The review provides a clear framework for understanding algorithm applicability and selection across diverse scenarios, and aims to offer theoretical references for developing efficient, robust path planning technologies tailored to complex dynamic environments in future inspection robots.

KEYWORDS

Path planning; Mobile robots; Photovoltaic inspection

1. INTRODUCTION

With the widespread application of mobile robot technology in industrial automation, intelligent services, emergency rescue, and other fields, path planning has become a critical interdisciplinary research topic at the intersection of artificial intelligence and robotics as the core component of autonomous navigation. From AGV scheduling in warehouse logistics to drone delivery in complex urban scenarios, path planning algorithms must not only ensure path optimality and safety but also address practical challenges such as dynamic obstacles, high-dimensional environments, and multi-robot collaboration. Traditional algorithms (e.g., A*, Dijkstra) excel in static environments due to their theoretical rigor but face limitations in dynamic adaptability and computational efficiency. Sampling-based algorithms (e.g., RRT*, PRM) break through dimensional constraints via probabilistic approaches yet encounter bottlenecks in path quality and stability. Intelligent optimization algorithms (e.g., ant colony, particle swarm) possess global search capabilities but are constrained by convergence speed and parameter sensitivity.

In recent years, scholars have progressively advanced path planning from single-objective optimization toward multi-objective collaboration through strategies such as algorithm fusion, multi-modal perception fusion, and cross-layer optimization. Examples include the integration of dynamic replanning (D*) with reinforcement learning and energy consumption modeling driven by 3D semantic maps. Nevertheless, unifying efficiency, robustness, and interpretability remains an unresolved challenge. This paper systematically reviews three mainstream approaches to mobile robot path planning—traditional algorithms, intelligent algorithms, and sampling-based algorithms—

analyzing their core principles, improvement directions, and applicability boundaries. It further explores frontier trends like algorithm fusion, multi-sensor collaboration, and IoT-enabled architectures, aiming to provide theoretical references and technical foresight for autonomous navigation research in dynamic and complex scenarios.

2. PATH PLANNING ALGORITHMS

2.1. Traditional Planning Algorithms

These algorithms are primarily designed for known or static environments and do not consider dynamic environmental changes. Typically, they employ systematic search methods to compute paths based on mapped or grid-based environmental models.

Hart et al. proposed the A* (A-star Algorithm) 11. The A* algorithm is a widely used heuristic path search algorithm. It guides the search direction through an evaluation function:

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

g(n): Actual cost from the start node to the current node *n*.

h(n): Heuristic estimated cost from the current node *n* to the goal node.

f(n): Comprehensive priority of node *n*.

The Dijkstra algorithm, initially developed by Dijkstra in the mid-20th century, is a graph theory-based method. It calculates the shortest path from a source node to all other nodes by incrementally expanding the search scope. Applicable to weighted graphs with non-negative edge weights, its core idea is greedy selection: at each step, it selects the unprocessed node closest to the start node, updates the shortest distances for adjacent nodes, and gradually extends the shortest-path tree.

The introduction of the A* and Dijkstra algorithms marked milestones in path planning. Subsequent research has focused on enhancing computational efficiency and adaptability to complex environments. Key improvements include reducing search nodes, optimizing heuristic functions, and accelerating computation. Since A* is suitable for known or static environments, Stentz enhanced it by proposing the D* algorithm 22, which updates grid information near dynamic obstacles and allows heuristic transfer. Tang et al. refined traditional A* paths using filtering functions and smoothed them with B-spline curves, achieving shorter execution times and higher path quality 33. Zheng Yi et al. addressed the high failure rate of classical Dijkstra in complex constraints (e.g., sudden flight path changes) by introducing an improved Dijkstra algorithm. Their approach integrates a pre-search mechanism and normalized entropy weight method, enhancing backtracking capabilities and reducing computation time via an escape mechanism, thereby improving planning efficiency and reliability 44.

2.2. Sampling-Based Planning Algorithms

Sampling-based planning algorithms primarily include the Probabilistic Roadmap Method (PRM) and the Rapidly-exploring Random Tree (RRT) algorithm. Kavraki et al. proposed the PRM algorithm [5], which constructs nodes through random sampling in space and connects them to form a probabilistic roadmap, enabling optimal path searches from start to goal. It is a multi-query planning algorithm comprising two phases: learning and query.

To address the limitations of traditional PRM in handling narrow passages, Liu Yang et al. [6] introduced an improved PRM method. By integrating an artificial potential field, this approach exerts repulsive forces on sampling points within threat zones, relocating them to free space. This increases node density in narrow passages without additional sampling, accelerating roadmap construction. Experimental results confirmed that the enhanced PRM improves sampling efficiency, reduces path-planning time in narrow environments, and rapidly generates paths under sudden threats. Feng Ao et al. [7] tackled issues of uneven sampling distribution, low mapping efficiency, and path redundancy in traditional PRM. Their improvements include: Optimizing sampling using a 2D Sobol sequence to ensure uniform distribution. Classifying sampling points by neighborhood and applying connection constraints to reduce roadmap complexity. Adjusting node positions via a node translation optimization algorithm to approximate real-space optimal paths. Smoothing path turns with Bézier curves to align with robot kinematic constraints.

In 1988, Lavalle proposed the RRT algorithm, a stochastic sampling method capable of rapidly exploring high-dimensional spaces. It suits large-scale complex environments by incrementally building a search tree to connect start and goal points.

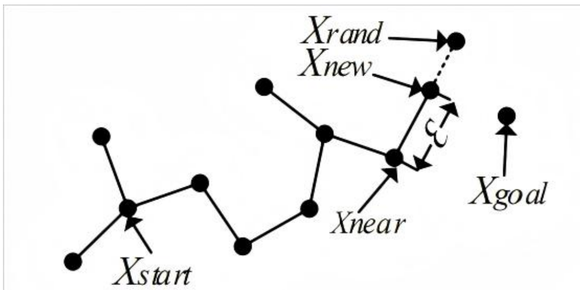

Figure 1. RRT Algorithm Path Planning Process

To overcome RRT’s low search efficiency and lack of path optimization, Karaman et al. [8] developed RRT, which optimizes paths through rewiring and parent reselection, achieving asymptotic optimality. Addressing RRT’s inefficiency, redundant nodes, and high path costs, Luo Jiyu et al. [9] proposed an enhanced RRT* variant. Key innovations include: Replacing fixed step sizes with global adaptive step-length determination. Implementing a regional sampling rejection strategy to reduce redundant nodes in overlapping areas. Optimizing planned paths to minimize cost and node count. Simulations demonstrated superior search capability, robustness, and environmental adaptability compared to standard RRT*.

2.3. Intelligent Optimization Algorithms

Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) represent classical intelligent optimization algorithms. Inspired by biological evolution, collective behavior, and ant foraging respectively, they are extensively applied to optimization, path planning, and solving complex problems.

The genetic algorithm, proposed by Bremermann, simulates natural selection and genetic evolution through selection, crossover, and mutation to search for optimal solutions. To address premature convergence and poor optimization capabilities in traditional GA, Song et al. [10] developed an enhanced path planning method. By designing a heuristic crossover operator and adaptive mutation operator, the improved algorithm demonstrates more rational path planning and enhanced convergence in simulations.

Particle swarm optimization mimics collective behaviors (e.g., bird flocks, fish schools) in search spaces, where particles progressively approach optima through individual-group information sharing. To mitigate PSO's susceptibility to local optima and population diversity loss in path planning, Chen et al. [11] proposed a Multi-strategy Fused PSO (MFPSO). This algorithm employs four performance-enhancing strategies:

(1) Updating particle positions via a perpendicular bisector algorithm to accelerate convergence;

(2) Generating explosion particles near optimal particles to escape local optima;

(3) Implementing linear dynamic inertia weight adjustment to strengthen search capabilities;

(4) Applying local search around global optima for path refinement.

Simulation results confirm MFPSO's superiority over conventional algorithms in path search.

Ant colony optimization emulates ant foraging behavior, where ants collaboratively identify shortest paths to food sources by depositing pheromones.

Widely adopted in dynamic path planning for mobile robots, ACO exhibits robustness but suffers from slow convergence and local optima due to its pheromone update mechanism. Xue et al. [12] introduced improvements including:

A directional heuristic function for intelligent node selection;

Cauchy distribution integration to enhance late-stage global search;

Optimized distance heuristic function for accelerated convergence;

Dynamically adjusted pheromone evaporation factor to improve global exploration;

Cubic B-spline curve smoothing for kinematic compliance.

Experimental results show 3% faster convergence, 12% shorter paths, and 76% fewer iterations. Other studies employ algorithm fusion strategies [13, 14]. Lu et al. [15] integrated ACO with artificial potential fields, designing a heuristic function based on resultant forces to guide path selection. This approach demonstrates effective obstacle avoidance, improved path optimality/safety, and significantly reduced convergence iterations.

3. COMPARATIVE ANALYSIS OF PATH PLANNING ALGORITHMS

Traditional path planning algorithms, represented by A* and Dijkstra, achieve optimal path solutions in static environments through graph-search frameworks. The A* algorithm integrates the actual cost $g(n)$ and heuristic estimate $h(n)$ to significantly narrow the search space, ensuring both efficiency and optimality in known environments. Dijkstra's algorithm progressively extends the shortest-path tree via a greedy strategy, guaranteeing global optimality. However, its $O((|V| + |E|)\log|V|)$ time complexity limits scalability in large-scale scenarios. To address poor dynamic adaptability, scholars have implemented incremental updates (e.g., D*), path smoothing (B-spline curves), and pre-search mechanisms (normalized entropy weight method). Despite these improvements, memory consumption and real-time performance remain bottlenecks.

Sampling-based algorithms (e.g., PRM, RRT) overcome dimensionality constraints through probabilistic sampling, proving more suitable for high-dimensional complex spaces. PRM constructs probabilistic roadmaps via random sampling, supporting multi-query planning but struggling with narrow passages. Enhancements like potential field guidance and Sobol sequence optimization improve node utilization. RRT rapidly explores unknown regions using randomized trees, while its variant RRT* achieves asymptotic optimality through rewiring. Adaptive step sizes and regional sampling rejection reduce redundant nodes, though post-processing path optimization remains necessary.

Intelligent optimization algorithms (GA, PSO, ACO) draw inspiration from biological behaviors to solve non-convex optimization problems via swarm intelligence. Genetic algorithms avoid local optima through crossover and mutation but require heuristic operators to mitigate premature convergence. Particle swarm optimization converges rapidly yet easily traps in local optima; integrating explosion particles and dynamic weights enhances its search capability. Ant colony optimization relies on pheromone positive feedback but suffers from slow convergence. Combining artificial potential field guidance and Cauchy distribution perturbations balances exploration and exploitation.

In summary, traditional algorithms excel in static environments, sampling-based methods offer greater scalability in high-dimensional dynamic spaces, and intelligent algorithms handle complex constraints through global search. These approaches exhibit complementary strengths, making fusion strategies (e.g., ACO + potential fields) and adaptive parameter design critical for performance enhancement.

Table 1. Comparative Summary of Path Planning Algorithms

Algorithm Type	Representative Algorithms	Core Advantages	Main Limitations
Traditional Planning Algorithms	A* Algorithm	Heuristic-guided rapid convergence, strictly optimal in static environments	Memory consumption increases drastically with node count
	Dijkstra Algorithm	Guarantees global shortest path, theoretically rigorous	Low computational efficiency, cannot handle negative-weight edges and dynamic changes
Sampling-Based Planning Algorithms	PRM	Efficient mapping in high-dimensional spaces, supports multi-query planning	Difficult path generation in narrow passages, high demand for initial sampling uniformity
	RRT*	Probabilistic completeness, adapts to complex dynamic environments	Path tortuosity requires re-optimization, stochasticity causes stability fluctuations
Intelligent Optimization Algorithms	Genetic Algorithm (GA)	Global search avoids local optima, flexible adaptation to multi-constraint conditions	Complex parameter tuning, high iterative computation cost
	Particle Swarm Optimization (PSO)	Fast convergence, simple implementation	Rapid population diversity decay, prone to premature convergence in high-dim spaces
	Ant Colony Optimization (ACO)	Strong distributed parallelism, good environmental adaptability	Sensitive to pheromone update strategies, slow convergence for large-scale problems

4. TRENDS IN PATH PLANNING ALGORITHM DEVELOPMENT

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The future development of path planning algorithms will focus on multi-dimensional collaborative innovation and scenario-specific adaptation, driving a paradigm shift from static isolated decision-making to dynamic intelligent collaboration. As application scenarios for mobile robots grow increasingly complex, algorithm design is breaking through traditional boundaries to form a new framework characterized by cross-method integration, cross-modal perception, and cross-layer optimization.

At the level of dynamic environment adaptability, incremental replanning strategies (e.g., improved local update mechanisms in D* algorithms) and multi-sensor fusion technologies (heterogeneous data complementarity from LiDAR, visual SLAM, and inertial navigation) are deeply integrated. This enables real-time construction of semantic environmental models, significantly enhancing response efficiency for drones and service robots in crowded areas and unexpected obstacle scenarios while reducing computational overhead from global searches.

Algorithmic architecture innovations manifest as deep coupling between traditional methods and intelligent optimization:

A collaborative framework combining heuristic search (A*) and reinforcement learning achieves end-to-end decision optimization in unknown environments;

Ant colony optimization introduces potential-field-guided pheromone distribution to accelerate convergence while avoiding local optima;

3D RRT* integrates adaptive step-size adjustment and B-spline trajectory smoothing to provide energy-efficient and motion-continuous solutions for underwater vehicles and urban air mobility.

For high-dimensional complex environments, the introduction of semantic GIS technologies and topological layering strategies allows path planning to incorporate terrain risks, energy consumption models, and real-time traffic flow beyond geometric constraints. This enhances the practicality and safety of industrial inspection robots and autonomous driving systems in complex scenarios.

Multi-robot cooperative planning relies on distributed swarm intelligence and edge-cloud collaborative computing architectures, implementing dynamic task allocation and computing resource optimization through IoT technologies. Examples include cluster scheduling based on contract net protocols combined with lightweight TinyML-enabled local decision-making, alleviating single-robot computational bottlenecks while ensuring real-time obstacle avoidance and energy efficiency in logistics sorting and disaster rescue scenarios.

The integration of green sustainability concepts further drives algorithms toward multi-objective optimization. Embedding carbon emission factors and mechanical wear models into path evaluation functions enables clean-energy robots and electric vehicles to balance efficiency with environmental friendliness.

Although hybrid strategies and collaborative computing dominate, continuous refinement of fundamental algorithms remains essential. Examples include enhancing global search capabilities in ant colony optimization through Cauchy distribution perturbations and reconstructing fitness functions in genetic algorithms using differential geometry theory. These foundational innovations establish robustness under complex constraints.

Looking forward, path planning will accelerate interdisciplinary convergence:

Quantum computing may solve high-dimensional non-convex optimization problems;

Neuro-symbolic systems could enhance algorithmic interpretability in safety-critical domains (e.g., healthcare, transportation);

Embedded ethical rules (e.g., emergency avoidance priorities for autonomous vehicles) will promote co-evolution of technology and social values.

These advancements will ultimately enable mobile robots to transition from functional tools to autonomous cognitive agents.

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