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A Review of Trajectory Planning and Path Tracking Methods for Mobile Robots

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Abstract. Driven by the rapid advances in artificial intelligence, autonomous driving, and intelligent manufacturing, mobile robots have been widely applied in industrial production and logistics transportation. Trajectory planning and path tracking are two core components of autonomous navigation, directly affecting the navigation safety, motion stability, and environmental adaptability of mobile robots. This paper reviews representative methods of the two core technologies. In terms of trajectory planning, traditional search algorithms, intelligent optimization algorithms, and other mainstream methods are systematically introduced. For path tracking, classical and intelligent control approaches are discussed and comprehensively compared. Furthermore, state-of-the-art research trends, including machine learning-based planning and control strategies, are briefly summarized. Existing research has shown that the integration of conventional methods and intelligent algorithms has become a pivotal research direction in this field. By analyzing the characteristics, advantages, limitations, and applicable scenarios of various methods, this paper provides a valuable reference for algorithm selection and integrated planning-control research of mobile robots.

Keywords: mobile robot, trajectory planning, path tracking, intelligent control, autonomous navigation

1. Introduction

With the growing use of mobile robots in different fields,autonomous navigation has become a core function of intelligent robotic systems [1]. Within this area,trajectory planning and path tracking are two basic parts [2]. Trajectory planning generates feasible and collision-free trajectories under environmental constraints,and path tracking allows robots to follow those trajectories accurately and complete navigation tasks.

As mobile robots are used more often in dynamic and complicated environments,navigation systems are expected to respond quickly,track more accurately,remain stable,and adapt to changing surroundings. Meeting all of these goals at the same time is difficult. In complex dynamic scenarios,a single algorithm usually cannot handle every requirement well,so combining planning and control methods has become a common direction in current research.

This paper reviews representative approaches to trajectory planning and path tracking for mobile robots. It compares typical algorithms in terms of their characteristics,strengths,limitations,and

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suitable application scenarios. Recent research trends are also discussed so that the review can offer some reference for algorithm selection and later work on autonomous navigation systems.

2. Trajectory planning methods

2.1. Traditional classical algorithms

Traditional trajectory planning algorithms generate optimal and collision-free paths under predefined motion constraints in known environmental maps. They usually rely on graph search,state traversal,or cost optimization.

2.1.1. Dijkstra and A* algorithms

Dijkstra and A* are typical graph-search algorithms for trajectory planning. Dijkstra searches the whole graph to find the global optimal path,but the computational cost rises sharply in large-scale environments [3]. A* improves search efficiency by adding a heuristic function to guide the search toward the target node [4]. For this reason,it is widely used in autonomous driving and robot navigation. Even so,its performance still depends heavily on how the heuristic function is designed,and in complex environments the generated path may not be smooth.

2.1.2. Bionic intelligent trajectory planning algorithms

Bionic intelligent algorithms,such as genetic algorithms,ant colony optimization,and particle swarm optimization,carry out trajectory planning by simulating natural evolution and collective biological behavior [5-7]. These methods usually have strong global search ability and good adaptability,so they are often used in complex and dynamic environments. But there are limits. Their performance is sensitive to parameter settings,and they may converge slowly or fall into local optima.

2.2. Sampling-based trajectory planning algorithms

Sampling-based trajectory planning algorithms build path search structures through random sampling in the robot state space,without fully discretizing the environment. This makes them different from graph-based methods. They have been widely applied in mobile robots,autonomous driving,and manipulator motion planning.

2.2.1. Rapidly-exploring random tree (RRT) algorithm

The rapidly-exploring random tree (RRT) is a sampling-based single-query trajectory planning algorithm that gradually expands a search tree through random sampling [8]. Because it does not require complete environmental modeling,RRT has strong space exploration ability and is often used in real-time and high-dimensional motion planning. Its weaknesses are also clear: the generated path can contain redundant nodes,path smoothness is often poor,and global optimality cannot be guaranteed.

2.2.2. Probabilistic roadmap (PRM) algorithm

The probabilistic roadmap (PRM) algorithm builds a roadmap by randomly sampling collision-free nodes and connecting them through local planning strategies [9]. Unlike single-query planning

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algorithms such as RRT,PRM separates offline construction from online query,so it is better suited to repeated planning tasks in static environments. Even so,its path search performance can drop when the sampling distribution is uneven or when the environment changes over time.

2.3. Artificial potential field method

The artificial potential field (APF) method is a classical trajectory planning approach. It guides robot motion through the combined effect of the attractive force from the target and the repulsive force from obstacles [10]. Because the method has a simple structure,low computational cost,and good real-time performance,the APF algorithm is widely used in local path planning and dynamic obstacle avoidance tasks. The main problem is that the traditional APF method can easily fall into local minima,and in some cases the target becomes unreachable. These issues blueuce its effectiveness in complex environments.

2.4. Hybrid planning methods

Because each planning algorithm has its own limits,hybrid planning methods have become a common way to improve overall planning performance. The basic idea is to combine different methods so that one algorithm makes up for what another lacks. In practice,this can improve global path quality,real-time response,and the ability to adapt to the environment.

A typical example is the combination of A* and the artificial potential field (APF) method [11]. Here, A* handles global path planning,while APF deals with local obstacle avoidance. The roles are clear. Compared with using only one algorithm, this combination usually gives better planning results in complex environments.

At the same time,hybrid planning methods often increase computational complexity and make parameter tuning harder. They can also be more difficult to implement,which still limits their wider use and needs further study.

Table 1. Comparison of typical trajectory planning algorithms for mobile robots

Method Classification	Representative Algorithm	Core Idea	Advantages	Disadvantages	Application Scenarios
Graph Search Algorithms	Dijkstra	Traverse graph nodes to obtain the shortest path	Global optimality; stable performance	High computational complexity	Small-scale static environments; offline planning
	A*	Heuristic-guided graph search	High efficiency; near-optimal solution	Heuristic-dependent; poor path smoothness	Grid-map navigation; autonomous driving
Bionic Intelligent Algorithms	Genetic Algorithms	Simulate biological evolution for path optimization	Strong global search ability; low model dependence	Slow convergence; parameter sensitivity	Multi-objective optimization; constrained planning

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Table 1. (continued)

Bionic Intelligent Algorithms	Ant Colony Optimization	Search paths through pheromone updating	Good adaptability; robust performance	Low initial efficiency; premature convergence	Multi-robot cooperation; complex environments
	Particle Swarm Optimization	Iterative optimization based on swarm cooperation	Fast convergence; simple implementation	Easily trapped in local optima	Continuous-space optimization; trajectory optimization
Sampling-Based Planning Algorithms	RRT	Randomly sample and expand a search tree	Fast exploration; suitable for high-dimensional spaces	Redundant paths; non-optimal solutions	Real-time planning; robotic manipulators
	PRM	Randomly sample nodes to construct a roadmap	Efficient repeated queries	Sensitive to sampling quality	Static environments; repeated planning tasks
Local Planning Algorithms	Artificial Potential Field (APF)	Motion guided by attractive and repulsive forces	Simple implementation; high real-time performance	Local minima; target-unreachable problem	Local obstacle avoidance; dynamic environments
Hybrid Planning Algorithms	A*-APF	Combination of global planning and local obstacle avoidance	Improved adaptability and planning performance	High complexity; difficult parameter tuning	Complex dynamic environments

3. Path tracking control methods

3.1. Traditional control methods

Traditional path tracking control methods mainly establish the relationship between robot motion states and reference trajectories. The control law is designed according to path errors, geometric constraints, or system models to achieve stable trajectory tracking for mobile robots.

3.1.1. PID control

PID is a classical feedback control method that reduces tracking errors through proportional, integral, and derivative actions [12]. It is widely used for its simple structure, low cost and practicality, but relies heavily on parameter tuning and performs poorly in nonlinear dynamic environments [13].

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3.1.2. Pure-pursuit and stanley methods

Pure-Pursuit and Stanley are representative geometry-based path tracking methods [14, 15]. Pure-Pursuit tracks the reference path by selecting a look-ahead target point and calculating the corresponding steering command. In contrast, Stanley simultaneously considers heading and lateral errors, achieving higher tracking accuracy under high-speed or variable-curvature conditions. However, Pure-Pursuit may suffer from large tracking errors on sharp curves, while Stanley is sensitive to controller parameters and may cause oscillations at low speeds.

3.1.3. Optimal and robust control

Representative optimal control methods include linear quadratic regulator (LQR) and model predictive control (MPC), while sliding mode control (SMC) is a widely used robust control strategy. LQR provides efficient optimal feedback control but relies on accurate system models [16]. MPC can explicitly handle system constraints and predict future states, although its computational burden is relatively high [17]. SMC exhibits strong robustness against uncertainties and disturbances but may suffer from chattering problems [18]. These methods achieve higher tracking accuracy and stability at the cost of increased computation.

Table 2. Comparison of typical path tracking algorithms for mobile robots

Method Classification	Representative Algorithm	Core Idea	Advantages	Disadvantages	Application Scenarios
Feedback Control	PID	Error-based feedback control	Simple; easy to implement	Parameter-sensitive; limited robustness	Low-speed tracking; velocity control
Geometric Control	Pure-Pursuit	Look-ahead point tracking	Low computational cost; simple implementation	Sensitive to look-ahead distance; poor performance on sharp curves	Low- and medium-speed tracking
	Stanley	Lateral and heading error control	Good high-speed performance	Parameter-sensitive; low-speed oscillation	Medium- and high-speed tracking
Optimal Control	LQR	Optimal state feedback control	High accuracy; efficient computation	Model-dependent; requires full-state feedback	Linear systems; precise tracking
	MPC	Predictive optimization control	Constraint handling; predictive capability	High computational cost; model-dependent	Complex dynamic environments
Robust Control	SMC	Sliding mode-based control	Strong robustness; disturbance rejection	Chattering; complex parameter tuning	Nonlinear systems; uncertain environments

3.2. Intelligent control methods

Intelligent control methods have become an important research direction for mobile robot path tracking. Compared with traditional model-based approaches, intelligent control enhances system adaptability via learning and environmental interactions.

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3.2.1. Fuzzy control

Fuzzy control is a typical intelligent control method based on fuzzy logic and expert experience, which can work effectively without accurate system mathematical models [19]. Owing to its good adaptability to nonlinear and uncertain systems, it is widely adopted in mobile robot path tracking research. However, its control effect relies heavily on the design of fuzzy rule bases, and the construction difficulty and complexity of such rules will rise rapidly with the expansion of system scale.

3.2.2. Neural networks and reinforcement learning

Neural networks and reinforcement learning are mainstream data-driven control approaches in robot research [20, 21]. These methods learn optimal control strategies from data and environmental interaction, possessing strong adaptability to complex and dynamic working environments. In practical applications, they still have prominent drawbacks: they require a large amount of training data and sufficient computing resources, and the low interpretability and unstable reliability of the models remain urgent problems to be solved.

3.3. Hybrid control strategies

Hybrid control strategies combine the merits of traditional and intelligent control methods to enhance the tracking accuracy, robustness and environmental adaptability of mobile robots. Common hybrid control forms include fuzzy PID control, neural network-assisted MPC and reinforcement learning-based feedback control [22]. Although these composite strategies can greatly improve comprehensive control performance, they also bring higher computational complexity and greater difficulty in practical engineering implementation.

4. Frontier developments and challenges

Driven by the rising demand for autonomous mobile robot operation in intricate and changeable working scenarios, machine learning-based planning and control, safety-oriented autonomous navigation and multi-robot collaborative planning have gradually become three mainstream research directions in the field of mobile robotics. The typical application scenarios and core technical challenges of the above research fields are summarized in Table 3.

Table 3. Typical application scenarios and challenges of frontier technologies for mobile robots

Research Direction	Typical Applications	Representative Methods	Key Problems Addressed	Challenges
Machine Learning-Based Planning	Autonomous driving; unknown environment exploration	Deep reinforcement learning (DRL); imitation learning; end-to-end learning	Improve autonomous decision-making and environmental adaptability	High training cost; large data requirements
Safety-Critical Motion Planning	Autonomous driving; medical assistance	Control barrier functions (CBF); MPC; formal verification	Ensure motion safety and system reliability	Balancing real-time performance and safety constraints

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Table 3. (continued)

Multi-Robot Cooperative Planning	Warehouse logistics; intelligent transportation	Multi-agent reinforcement learning (MARL)	Improve cooperation efficiency and task allocation	Communication constraints; high computational complexity

4.1. Machine learning-driven planning and control

Machine learning technology has been widely applied and developed in the research of mobile robot planning and control, forming a vital research branch in this field [23]. Typical technical frameworks cover deep reinforcement learning, imitation learning and end-to-end learning. Such data-driven technologies effectively optimize the autonomous decision-making ability and environmental adaptation performance of mobile robots through iterative training based on massive sample data. Even so, this series of methods still has obvious application limitations. Apart from the dependence on a large volume of training data and high computing power, unstable operating state and insufficient safety performance are still the main technical bottlenecks restricting its large-scale engineering application.

4.2. Safety-critical motion planning

Safety-critical motion planning is dedicated to guaranteeing the safe and reliable operation of mobile robots, which is widely required in autonomous driving, medical auxiliary robots, human-robot interaction and other high-risk application scenarios [24]. At this stage, the mainstream research methods mainly include control barrier functions (CBF), model predictive control (MPC), formal verification technology and fault-tolerant control methods. The biggest difficulty in practical research lies in how to achieve a reasonable balance between strict safety constraint guarantees and high real-time response performance under dynamic and uncertain environmental conditions.

4.3. Multi-robot cooperative planning

The research of multi-robot cooperative planning mainly involves multiple core contents including intelligent task allocation, real-time motion coordination, inter-robot information interaction and collaborative obstacle avoidance [25, 26]. The introduction of multi-robot collaborative mechanisms can effectively break through the capacity limitation of single-robot operation, thereby significantly improving the overall working efficiency and task completion quality of the robot system. Nevertheless, practical engineering applications still face many obstacles, among which limited communication conditions, complex dynamic environmental interference and high algorithm computational complexity are the key challenges that need to be solved urgently.

5. Conclusion

This paper reviews two key technologies in mobile robot autonomous navigation: trajectory planning and path tracking. Different algorithms exhibit distinct advantages and limitations in terms of real-time performance, tracking accuracy, environmental adaptability, and computational complexity. Consequently, hybrid planning and hybrid control strategies have become important research directions to boost overall navigation performance. In addition, emerging research topics including machine learning-based planning and control, safety-critical motion planning, and multi-

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robot cooperative planning are summarized. With the rapid advancement of autonomous driving, intelligent manufacturing and logistics systems, mobile robots are moving toward higher autonomy, intelligence and coordination. Future research will focus on integrating intelligent algorithms with traditional planning and control schemes to enhance environmental adaptability, operational safety and real-time performance under complex working conditions.

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