Path Planning Algorithm for Intelligent Robot

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Abstract. The task of intelligent robot path planning is to automatically generate the optimal motion path from the starting point to the target point on the basis of achieving safety, efficiency, and energy balance. The development of related technologies has improved the adaptability and efficiency of path planning, but it still faces challenges such as incomplete multi algorithm collaboration mechanisms, poor real-time response capabilities in dynamic environments, and difficulty in balancing computational resource consumption and path optimization effects. This article first divides algorithms into four perspectives: traditional algorithms, sampling based algorithms, biomimetic intelligent algorithms, and artificial intelligence driven algorithms. Typical algorithms are selected to analyze the principles and applicable scenarios of various algorithms, with a focus on studying the improvement approaches of emerging algorithms such as deep reinforcement learning. The feasibility of multi algorithm fusion is examined, the challenges faced by technology are summarized, various problems to be solved are sorted out, and future research directions are discussed. Intelligent robot path planning has become a hot research topic, and efficient and adaptive algorithms continue to emerge, which will extend to a wider range of directions in the future.

Keywords: Path Planning, Algorithm, Intelligent Robot.

1 Introduction

As a core device in modern industry and service fields, intelligent robots rely on efficient path planning technology for their autonomous mobility. With the rapid development of intelligent manufacturing and smart services, the application scenarios of robots have extended from structural factories to complex dynamic spaces such as shopping malls and hospitals. The core challenge that path planning algorithms need to solve is how to enable robots to independently plan the optimal motion path from the starting point to the target point while achieving a balance between safety, efficiency, and energy consumption [1]. If this technological bottleneck is broken through, it will have significant implications for improving the quality of robot task completion and reducing operation and maintenance costs.

The current path planning algorithms can be divided into traditional methods and intelligent optimization methods. As for traditional algorithms, Dijkstra and A * rely on building the topology of the environment map to implement heuristic search. In

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known static environments, the computational efficiency is high [2, 3], but relying on accurate modeling methods makes it difficult to deal with dynamic obstacles [4]. Although the D * algorithm can achieve dynamic reprogramming, its efficiency is limited by complex environments. Probabilistic Roadmap Method (PRM) and Fast Scaling Random Tree (RRT), which use sampling methods, are suitable for high-dimensional scenarios. PRM is suitable for static multi query situations, while RRT is good at dynamic single shot programming. Biomimetic intelligent algorithms, such as Genetic algorithm (GA) and Ant colony algorithm (ACO) use simulated biological behavior to achieve optimization goals, but face problems such as slow convergence speed. Reinforcement learning and neural networks driven by artificial intelligence do not require pre-existing knowledge. Liu Zhirong et al. improved memory replay and improved the convergence speed of dynamic scenarios [5]. However, existing research still has shortcomings in multi algorithm collaboration, dynamic response, and resource balance.

This article begins by systematically organizing the classification system and development trajectory of path planning algorithms. Then, it compares and analyzes the principles and applicability of traditional algorithms and intelligent optimization algorithms, considers improvement measures for emerging algorithms such as deep reinforcement learning, and uses typical application cases to verify the feasibility of multi algorithm integration. Finally, it summarizes the technical challenges faced and looks forward to future research trends.

2 Classification and Principles of Path Planning Algorithms

2.1 Sampling Based Algorithm

Probabilistic Roadmap Method. The Probabilistic Roadmap Method (PRM) aims to achieve efficient multi task planning in a known static environment, but needs to address the issues of insufficient sampling in narrow channels and poor real-time updating of dynamic roadmaps. The process is as follows: first, randomly sample and generate a set of nodes in free space, filter out collision nodes; Then, using nearest neighbor strategies such as K-D trees, collision free edges are constructed to form a connected graph; Finally, connect the starting and target points to the graph and use Dijkstra's algorithm to search for the path. The advantage of PRM lies in its ability to reuse preprocessed roadmaps, making it suitable for static multi query scenarios such as industrial robotic arms; However, narrow passages are prone to failure and have poor adaptability to dynamic environments. Xue Guanghui et al. improved the PRM algorithm by introducing the artificial potential field method in the construction stage and integrating the D * Lite algorithm in the query stage, which to some extent improved the safety of path planning and the success rate and efficiency of the algorithm. When obstacles suddenly appear, the improved PRM algorithm can achieve path replanning [6].

Rapidly-exploring Random Tree. The Fast Scaling Random Tree (RRT) family focuses on single planning in dynamic or unknown environments, requiring rapid response to environmental changes and facing challenges such as path redundancy and slow high-dimensional convergence. The standard RRT takes the starting point as the root node, and constructs a path by cyclically sampling the target bias point, locating the nearest neighbor node, and extending collision free new nodes until it reaches the vicinity of the target point. This "growth style" strategy gives it probabilistic completeness and allows for local reprogramming in dynamic scenes [7]; RRT * achieves asymptotic optimization through rewiring, while heuristic bias sampling and dynamic step size adjustment improve high-dimensional efficiency. Yu Mengxin et al. proposed target biased sampling strategy, node optimization strategy, dynamic step size strategy, and path pruning strategy based on the RRT algorithm, which improved path quality and shortened path seeking time [8].

2.2 Biomimetic Intelligent Algorithm.

Ant Colony. Ant colony algorithm (ACO) solves discrete space path optimization (such as TSP problem) by utilizing group collaboration to enhance optimization ability, but it has problems such as slow convergence and blind search in the initial stage. It simulates the communication mechanism of ant pheromones: ants randomly move and release pheromones that are positively correlated with path quality. Subsequently, ants select paths based on pheromone concentration and heuristic information, while avoiding local optima through pheromone volatilization. The distributed nature of ACO makes it highly parallel and fault-tolerant, making it suitable for warehouse AGV planning; Elite strategies or local search algorithms need to be introduced to improve convergence efficiency. Yuan Junhui et al. fused target oriented Euclidean distance and Chebyshev distance in the early stage, introduced normal distribution in the heuristic function, added reward and punishment strategies in the pheromone update mechanism, combined with adaptive pheromone volatilization factor dynamics, and finally improved the algorithm through pruning operation, improving the running efficiency in time [9].

Genetic Algorithm. Genetic algorithm (GA) excels in continuous space multi-objective optimization (such as unmanned vehicle trajectory smoothing), achieving global optimization through simulating natural selection, but it has issues with premature convergence and parameter sensitivity. It transforms path planning into population evolution: initializes a random path population, calculates fitness (path length, smoothness, etc.), selects high fitness individuals to cross and generate new paths, maintains diversity through mutation, and iterates to convergence. GA has strong global search capability and can handle multi-objective problems. Zhang et al. introduced a simulated annealing algorithm to improve the genetic algorithm, which can more effectively and quickly solve path planning problems in multi-objective situations [10].

2.3 Artificial Intelligence Driven Algorithm

Reinforcement Learning Algorithm. The path planning algorithm driven by artificial intelligence achieves intelligent decision-making through autonomous learning and environmental interaction. Its core is to handle decision optimization problems in unknown dynamic environments. Reinforcement learning and neural networks together form the core method system, and the two are combined to form a "perception decision" closed loop, enhancing planning capabilities in complex scenarios.

The basic goal of reinforcement learning algorithms is to enable robots to optimize decision strategies through trial and error learning in unknown environments, balancing the exploration of new paths with relying on known paths. Q-learning faces the dilemma of dimensionality disaster, with slow convergence speed in complex environments, while deep reinforcement learning requires high computational resources. Q-learning, as a classic model free reinforcement learning algorithm, implements policy optimization by constructing a state action value function (Q-table). The core process consists of three steps: environment interaction, reward feedback, and Q-value update. The robot selects actions based on the current state, receives rewards from the environment after execution, and updates the Q-value according to the Bellman equation. Pan Qitao et al. used a radial basis function (RBF) network to approximate the action value function of the Q-Learning algorithm based on traditional algorithms. They balanced the exploration and utilization ratio by dynamically adjusting the greedy factor, and increased the robot's selectable actions, shortening the path, reducing inflection points, and algorithm training epochs [11].

Deep Q-network (DQN) replaces the Q-table with a convolutional neural network, adopts experience replay and fixed target network technology, significantly enhancing the effectiveness of the algorithm in continuous state space. Xie Tian et al. proposed the R-D3QN algorithm, which constructs a dual network architecture, designs a temporal priority experience replay mechanism, and combines the spatiotemporal feature extraction ability of long short-term memory networks (LSTM) to propose a multi-stage exploration strategy based on simulated annealing. This improves the average reward of the algorithm and reduces the number of convergence and collision times [12]. Yu Xiaomin et al. proposed the C-RD3QN algorithm, which modified the convolutional layer to a residual network structure based on the D3QN algorithm. The action value function was estimated using the action advantage function in the competitive network structure, and combined with the state value function and reward value to achieve better path planning [13]. Deep Deterministic Policy Gradient (DDPG) further combines the Actor Critic framework, making it suitable for high-dimensional path planning in continuous action spaces. The dual network structure and soft update mechanism effectively ensure a smooth training process. On the basis of DDPG, Zhang Qingling et al. introduced a dueling network to improve accuracy, optimized the design of reward functions to guide mobile robots to move more efficiently and reasonably, and separated a single experience pool into a dual experience pool. They also adopted a dynamic adaptive sampling mechanism to improve the efficiency of experience replay, enhance the stability of model training, and improve the efficiency and accuracy of mobile robot path planning. Near end policy optimization (PPO) balances exploration and utilization through policy constraint mechanisms, exhibiting better robustness in dynamic obstacle avoidance scenarios. The advantage of this type of algorithm is that it can learn autonomously without prior knowledge of the environment, but its training phase requires a large amount of interactive data, and the tuning of hyperparameters has a significant impact on its performance. Qi Xuan et al. improved the PPO algorithm for Automated Guided Vehicles (AGVs) by using a multi-step action selection strategy and a multi task scheduling optimization algorithm, which shortened the path and improved efficiency [14].

Neural Network Assisted Planning. Reinforcement learning focuses on autonomous optimization of decision-making strategies and is suitable for real-time response in dynamic environments; Neural networks can enhance the abstract grasp of environmental features, which is beneficial for improving the accuracy of planning. Neural network assisted planning mainly solves the problem of feature extraction and time series prediction in complex environments, which requires transforming raw sensor data into relevant information for decision-making. However, it has the drawbacks of high computational resource consumption and poor black box decision interpretability. Convolutional neural networks (CNNs) use multi-layer convolutional kernels to extract deep features from environmental raster maps, transforming raw sensor data into high-dimensional semantic representations. Common application processes include: using encoder decoder structures to achieve environmental semantic segmentation and obtain heat maps of passable areas; Utilizing attention mechanisms to make dynamic obstacle features more prominent; The final output is a set of feature vectors related to path cost. Recurrent neural networks (RNNs) are particularly adept at dealing with temporal dependencies in path planning. Their gating units, such as LSTM, can model the temporal characteristics of motion trajectories. When service robots perform navigation tasks, RNNs use historical path sequences to predict pedestrian movements and achieve proactive obstacle avoidance planning. However, current research is gradually improving the computational efficiency and interpretability of neural networks through knowledge distillation, lightweight network design, and other means.

3 Algorithm Comparison

Table 1. Comparison Table of Path Planning Algorithms

Category	name	theory	advantage	shortcoming
Sampling based algorithm	Probabilistic Roadmap Method	Random sampling is used to construct a probability roadmap, and the path is obtained through graph search.	Suitable for high-dimensional spaces; Preprocessed can be	The dynamic environment needs to be restructured; Low sampling efficiency in

			queried repeatedly.	narrow channels.
	rapidly-exploring random tree	Incremental construction of random trees accelerates convergence by biased target sampling.	Adapt to dynamic environments; Probability completeness	The path may not be smooth; Slow convergence in high-dimensional space
Biomimetic intelligent algorithm	Genetic Algorithm	Path population evolves iteratively through selection/crossover/mutation	Global optimization; Multi objective processing	Premature convergence; high computational cost
	Ant colony	Accumulation of pheromones guides path selection, volatilization mechanism prevents rigidity.	Distributed computing; Adapt to dynamic changes; Self organization and strong robustness	Blind search in the early stage; High memory consumption; Easy to fall into local optima
Artificial intelligence driven algorithm	DQN	CNN extracts environmental features and Q-learning optimizes action strategies	End to end learning; Adapt to complex perception	The demand for training data is high; Difficulty in reward design
	DDPG/PPO	Actor Critic framework for handling continuous action spaces	Adapt to high-dimensional control; Strong strategic stability	Hyperparameter sensitivity; Simulation reality gap
	CNN+RNN	Fusion of CNN spatial encoding and RNN temporal prediction	Semantic environment understanding; Dynamic obstacle prediction	Black box decision-making; Dependency on annotated data

As shown in Table 1, traditional algorithms can find the complete optimal path, which is relatively simple and efficient, but are mainly used in static environments where the environment is known. The random sampling algorithm can be used for unknown high-dimensional spaces and has high planning efficiency, but its path may not be smooth and its quality may be unstable. The biomimetic evolutionary algorithm is used for discrete multi-objective programming, which has strong robustness, but the convergence speed is fast and may fall into local optima. Artificial intelligence algorithms can adapt to unknown environments, but their training costs are high and the training process is complex. Compared to traditional algorithms, random algorithms have higher applicability dimensions, and their adaptability to unknown environments is further enhanced in biomimetic and artificial intelligence algorithms. In terms of real-time performance (dynamic unknown environment), reinforcement learning is superior; In high-dimensional continuous spaces, the RRT series has the highest efficiency; In multi-objective optimization, biomimetic evolutionary algorithms are sensitive to parameters.

4 Problems to be Solved and Future Research Directions

The efficient real-time planning of dynamic environments faces response delays and replanning stability issues in extreme scenarios. Traditional algorithms need to recalculate the global path when the environment suddenly changes, resulting in a decrease in real-time performance. Although sensor fusion and LSTM have been effective in predicting obstacle trajectories, there are limitations, such as accumulated errors and high computational costs. In the future, quantum computing can be explored to accelerate path search.

In the optimal search of a high-dimensional constrained space, the planning of robotic arms is inefficient due to the curse of dimensionality. Existing GNN collision agent models and hierarchical planning strategies rely on training data, and in the future, people can learn from biological neural systems to develop pulse neural network algorithms to improve efficiency.

Multi machine collaboration and human interaction suffer from communication limitations leading to group deadlocks and social norm conflicts. The generalization ability of distributed protocols based on game theory is limited, and achieving cross scenario knowledge sharing through federated learning may be a feasible direction in the future; In the future, multi-agent reinforcement learning will also break through communication deadlocks and social conflicts, optimizing the collaborative security and efficiency of human-machine groups through distributed credit allocation, dynamic attention mechanisms, and inverse reinforcement learning.

5 Conclusion

Intelligent robots are widely used in the industrial and service fields, with scenarios expanding from structural factories to more complex dynamic spaces. Based on this, path planning needs to balance safety, efficiency, and energy consumption. The existing algorithms have problems such as insufficient multi algorithm collaboration, poor dynamic response, and difficulty in balancing resources and optimization. This article first classifies and sorts out algorithms, dividing existing algorithms into three categories: sampling based algorithms, biomimetic intelligent algorithms, and artificial intelligence driven algorithms. It analyzes typical algorithm principles and applicable scenarios, compares them, studies emerging algorithm improvement approaches such as deep reinforcement learning, and explores the feasibility of multi algorithm fusion. In the future, the development of intelligent robot path planning requires optimizing algorithm performance, promoting the integration of multiple algorithms and the formation of adaptive architectures, breaking through the bottleneck of perception decision-making through interdisciplinary fusion, balancing algorithm innovation, hardware adaptation, and scenario implementation, and achieving autonomous, efficient, and safe movement of robots.

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