Progress of Deep Learning in Path Planning for Mobile Robots

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Abstract. Mobile robot path planning is a key technology in the field of intelligent robotics, and its performance directly affects the autonomy and reliability of robots in dynamic environments. Traditional algorithms rely on accurate environment modelling, which makes it difficult to cope with real-time changes in complex scenes. Deep learning techniques significantly improve the robustness and generalisation ability of path planning through end-to-end learning and autonomous feature extraction. This paper reviews the basic concepts of mobile robot path planning and analyses the recent advances of deep learning in path planning, including path optimization based on deep reinforcement learning, deep neural network-assisted path generation, and the fusion strategy of traditional methods and deep learning. Subsequently, this paper discusses the major challenges currently faced, such as computational complexity, model generalisation capability, and dynamic environment adaptation, and proposes future directions in the context of existing research, including lightweight models, cross-environment migratory learning, and multi-sensor fusion. This review aims to provide a comprehensive reference for researchers to promote the further application and development of deep learning in mobile robot path planning.

Keywords: Mobile Robot, Path Planning, Dynamic Environment, Deep Learning

1 Introduction

In recent years mobile robots have been widely used in many fields such as industrial automation, intelligent transport, service robots, and unmanned systems, and their autonomous navigation and path planning capabilities directly affect their task execution efficiency and safety. The core objective of path planning is to compute the optimal or sub-optimal path from the starting point to the goal point based on the environment information and to update the planning results in real time in a dynamic environment. Traditional path planning methods, such as A*, Dijkstra, and rapidly expanding random trees (RRT), have good performance in specific scenarios, but their limitations gradually emerge in complex dynamic environments, high-dimensional spaces, or high computational load tasks. In recent years, the rapid development of deep learning has provided new solutions for path planning. Deep Reinforcement Learning,

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DRL excels in handling high-dimensional state spaces, autonomous decision making and complex environment adaptation. In addition, deep neural networks (DNNs) are widely used for path optimisation, environment sensing and uncertainty prediction, which further enhance the autonomy of mobile robots. Therefore, studying the application of deep learning in mobile robot path planning is not only of theoretical value but also of great significance to the development of intelligent robotics.

In recent years, deep learning has been applied to path planning in the following ways:

1) Reinforcement Learning Driven Path Optimisation: Xu et al. proposed a self-supervised learning method for efficient robot path planning in dynamic scenarios, DRL enables robots to learn optimal paths autonomously in dynamic environments through a self-supervised learning strategy [1].

2) Neural network-assisted path generation: Chen et al. proposed a deep imitation learning method for high-speed guidance of mobile robots in congested environments, and techniques such as CNNs and Recurrent Neural Networks (RNNs) can be used for path estimation and environment modelling to improve the computational efficiency of path planning [2].

3) Combination of classical methods with deep learning: Anderson et al. proposed an approach combining search-based algorithms and deep learning for neural network motion planning for fast path generation. Combining classical algorithms (e.g., RRT*) with deep learning models improves the efficiency and stability of path planning [3].

This paper analyse recent advances in deep learning for path planning, including path optimisation based on deep reinforcement learning, deep neural network-assisted path generation, as well as fusion strategies between traditional methods and deep learning to explore the main challenges faced so far, such as computational complexity, model generalisation capability and dynamic environment adaptability, and the author hope to propose future directions for development, including lightweight models, cross-environmental migratory learning and multi-sensor fusion, etc. This review aims to provide a comprehensive reference for researchers to promote the further application and development of deep learning in mobile robot path planning.

2 Overview of Mobile Robot Path Planning

2.1 Definition and Classification of Route Planning

Path planning is the computation of optimal or suboptimal paths from a starting point to a goal point in a known or perceived environment, based on specific goals and constraints. Path planning plays a central role in areas such as mobile robots, autonomous vehicles, and UAVs, and aims to ensure that robots can perform navigation tasks in complex environments, avoid collisions and try to optimise performance metrics such as task execution time and energy consumption.

2.1.1 Global path planning.

Global path planning is concerned with planning a complete path from a starting point to a goal point for a global map of the entire environment. Typical algorithms include the A* algorithm, Dijkstra's algorithm, and the rapidly expanding random tree (RRT). The advantage of global path planning is that the computed paths are usually more optimised, but the disadvantage is that it may not be able to cope with real-time changes in dynamic or incompletely known environments.

2.1.2 Local path planning.

Local path planning focuses on information about the current position of the robot and its surroundings, and adjusts the path in real time to avoid obstacles. Local path planning is usually based on sensor data and relies on online computation and dynamic adjustment. Commonly used algorithms include the artificial potential field method, the D*Lite algorithm, and the dynamic window method. Local path planning is suitable for highly dynamic or unknown environments but tends to have high computational complexity due to its reliance on real-time sensing.

2.2 Traditional Path Planning Methods

In traditional path planning, the most classical algorithms include A* algorithm, Dijkstra's algorithm and RRT.

2.2.1 A* algorithm.

A* algorithm is a heuristic search algorithm that was proposed by Hart et al. and is widely used for path planning in static environments [4]. The basic idea is to select the optimal path by estimating the cost from the starting point to the goal point. A* algorithm can provide more optimal solutions in many path-planning problems. A* algorithm has the advantage of planning a short route, simple to use, but is prone to poor path smoothness and many corner points. Li et al used an adaptive adjustment step algorithm and cubic Bessel curve optimization of the A* algorithm to solve the problem of searching a path with problems such as many turning points, large corners and long running time [5]. Jia Mingchao et al. used a more accurate search neighbourhood selection strategy, introduced the safety distance, and used an adaptive arc optimization method fused with the dynamic window method, which improved the algorithm's search orientation, path optimality, and obstacle avoidance ability [6].

2.2.2 Dijkstra's algorithm.

Dijkstra's algorithm (Dijkstra's algorithm) was first proposed by Dijkstra in 1956 and is widely used for the path planning of mobile robots. The algorithm searches for the nearest node by iterating outwards with the starting node as the centre, and takes it as the next node, and at the end of each iteration, updates the shortest distance between the starting node and all the traversed nodes, and finally obtains the shortest distance of the planned path. Dijkstra's algorithm has been widely used due to its high utility and robustness, but due to its undirected search characteristics, when the When the search environment is complex, the search nodes proliferate, the computational volume increases, the efficiency of the algorithm decreases, and the real-time performance is poor.

2.2.3 RRT.

The RRT algorithm was proposed by Professor LaValle of Iowa State University in 1998 and can be used in high-dimensional spaces in unfamiliar environments. The RRT algorithm forms a path by generating a randomly expanding tree, where the initial node is the root node of the tree, and leaf nodes are selected by random sampling, and when the selected leaf nodes contain the target node, a valid path is generated. The algorithm is efficient, but the planning path is not optimal, and the path is not smooth enough.

2.3 The Need for Deep Learning to Introduce Path Planning

As the complexity of the environment increases, especially in dynamic and unknown environments, traditional path planning methods are difficult to cope with large-scale environmental modelling and dynamic obstacle processing, and their computational ability and real-time performance are poor. Deep learning technology introduces new ideas for path planning, and deep learning technology is mainly reflected in the following aspects:

Handling of high-dimensional state spaces: traditional path planning methods usually rely on accurate environment models, which cannot effectively cope in high-dimensional spaces and dynamic environments. Deep learning, especially deep reinforcement learning (DRL), can effectively find optimal paths in high-dimensional state spaces through self-learning and reward mechanisms [7].

Adaptive capability: Deep learning models can be adaptively tuned with large amounts of training data, enabling the robot to dynamically update its path planning strategy based on real-time sensor data. This adaptive capability makes deep learning a powerful tool for dealing with dynamic obstacles and environmental changes.

Integration and generalisation capability: Deep neural networks can extract environmental features from multiple perspectives (e.g., vision, LIDAR, sonar, etc.) and perform multimodal fusion, thus improving the accuracy and reliability of path planning.

Therefore, combining deep learning and traditional path planning methods can improve computational efficiency and adaptability while ensuring path quality, especially in dynamic and complex environments with better performance.

3 Advances in Applications of Deep Learning to Path Planning

With the rapid development of deep learning technology, traditional path planning methods have gradually exposed their shortcomings in complex and dynamic environments, and deep learning is increasingly applied to mobile robot path planning. Deep learning techniques, especially Deep Reinforcement Learning (DRL), Convolutional Neural Networks (CNN), and Generative Adversarial Networks (GAN), can effectively deal with high-dimensional state space, complex dynamic obstacles, and multimodal information, thus significantly improving the efficiency and adaptability of path planning.

3.1 Deep Reinforcement Learning in Path Planning

Deep Reinforcement Learning (DRL), as a technique capable of autonomous learning and decision-making, has been widely used in path planning for mobile robots. DRL can efficiently deal with path planning problems in dynamic environments by continuously optimising its behavioural strategies through interaction with the environment.

1). Path planning optimisation: the application of DRL in path planning mainly focuses on optimising the decision-making process. Through the reward mechanism, the robot can gradually learn the optimal path. For example, Q-learning and policy gradient methods have achieved good results in unmanned vehicle path planning [8].

2). Complex Environment Adaptation: While traditional path planning methods often rely on predefined environment models, DRL can self-learn in unknown or dynamic environments, adapting to factors such as obstacles and environmental changes. This enables DRL to better cope with complex situations when dealing with robots with complex path-planning requirements such as unmanned vehicles and UAVs.

For example, the DRL-based Motion Planning Network (MPNet) proposed by Gupta et al. combines classical path planning methods and DRL techniques, enabling robots to efficiently complete tasks in dynamic environments. The method exhibits higher stability and adaptability in different scenarios through self-learning and optimisation strategies [9].

3.2 Neural Network-assisted Path Generation and Optimisation

DNNs are widely used for path generation and optimisation tasks in path planning. Unlike traditional methods, neural networks can learn efficient path-generation strategies from a large amount of training data and can better handle path-planning problems in variable environments.

3.2.1 Path generation and planning.

High-quality paths can be generated by training neural networks, especially convolutional neural networks (CNN) or recurrent neural networks (RNN). For example, CNNs can generate paths directly from visual data of the environment, while RNNs can handle continuous motion planning tasks [10]. These networks can generate smoother and more efficient paths for robots by learning the structure and dynamics of the environment.

3.2.2 Mixing methods.

Several studies have combined traditional path planning algorithms with deep learning models (e.g., neural networks) to improve the computational efficiency and optimisation quality of paths. The Neural RRT algorithm proposed by Zhang et al. optimises the traditional RRT algorithm by introducing a deep neural network, which retains the search advantage of the RRT* algorithm and improves the effectiveness of the path optimisation [1].

3.3 Path Planning Based on Imitation Learning

Imitation Learning (IL), which learns path-planning strategies by imitating expert demonstrations, has become another important application of deep learning in path planning. Unlike reinforcement learning, imitation learning does not require environmental interaction and long-term training but directly generates paths by learning from expert demonstrations.

3.3.1 Efficient navigation.

Deep imitation learning is widely used for efficient path planning, especially in complex or crowded environments. For example, Chen et al. proposed an efficient navigation method based on deep imitation learning, which can perform path planning in complex environments by imitating expert demonstrations. The method not only improves the planning speed but also reduces the consumption of computational resources in complex environments [2].

3.3.2 Real-time obstacle avoidance.

Imitation learning can generate obstacle avoidance strategies based on the behaviour of experts, enabling robots to update their path planning in real time in dynamic environments. This approach has a wide range of applications in the field of unmanned aerial vehicles and autonomous driving, which can effectively avoid collisions between robots and obstacles, and improve the safety and stability of task execution.

4 Performance Comparison of Traditional Path Planning Algorithms and Deep Learning Path Planning

The key performance indicators and advantages and disadvantages of some classic algorithms for traditional path planning and deep learning path planning are shown in Table 1.

Table 1. Performance comparison of traditional path planning algorithms and deep learning path planning

Performance indicators	A* algorithm (Traditional)	Dijkstra's algorithm (Traditional)	DQN (deep learning)	PPO (deep learning)

Planning time (ms)	50-200	100-500	20-150	10-100
Path length	shortest path	shortest path	approximate optimisation	approximate optimisation
computational complexity	O(nlogn)	$O(n^2)$	O(n)	O(n)
Dynamic environmental adaptation	Lower	Lower	High	High
Computing resource consumption	Lower	Lower	High (training required)	High (training required)
Applicability to large-scale environments	usual	usual	talented	talented

5 Current Challenges

Despite the significant progress made by deep learning techniques in path planning, there are still several challenges to be faced, especially for applications in dynamic and complex environments. The following are the main challenges currently faced when applying deep learning for path planning.

5.1 Treatment of High-dimensional State Spaces

Path planning problems usually involve high-dimensional spaces, especially in multi-degree-of-freedom robotic systems (e.g., unmanned vehicles or drones). Search and optimisation of high-dimensional state spaces is a major challenge for deep learning in path planning.

In high-dimensional spaces, traditional path planning algorithms (e.g., RRT and A*) need to traverse a huge search space to find the optimal path, while deep learning methods rely on a large amount of training data and computational resources for optimisation. This makes deep learning models in high-dimensional spaces, especially in the case of dynamic obstacles and multi-objective tasks, face training difficulties and high computational costs [11].

With the increase of dimension, the complexity of the path planning problem grows exponentially, and traditional methods are often difficult to deal with effectively, while deep learning faces the limit of its representation and generalisation ability in high-dimensional space. How to design efficient models and reduce computational complexity is a major challenge in current research [10].

5.2 Real-time and Computational Resource Issues

Deep learning methods, especially path planning based on reinforcement learning and deep neural networks, usually require long training times as well as large computational resources.

5.2.1 Long training time.

Methods such as deep reinforcement learning and imitation learning require extensive interaction and training in the environment, which is often a time-intensive process. Especially in practical applications, robots need to respond quickly to changes in the environment, and long training cycles may not be able to satisfy real-time demands [2].

5.2.2 High consumption of computing resources.

Deep learning models require large-scale datasets for training and high-performance computing hardware (e.g., GPUs) to support model training and inference. However, in practice, the consumption of computational resources may exceed the processing capacity of the robot system, limiting the practical application of deep learning algorithms [4].

5.3 Environmental Change and Generalisability Issues

The generalisation ability of deep learning models is an important issue currently faced in path planning. Training models usually rely on environment-specific data, but in practice, robots are often faced with a variety of different environmental variations.

5.3.1 Environmental uncertainty.

In dynamic and unknown environments, robots often must cope with rapidly changing obstacles, sensor noise, and environmental uncertainty. The static datasets used for deep learning model training may not be able to adequately model these changes, leading to path-planning failures for robots in real-world environments [8].

5.3.2 Cross-domain generalization.

Deep learning models are usually trained in a particular task or environment and are difficult to directly migrate to other environments or tasks. The models may not adapt well to different maps, obstacle configurations, or robot platforms [1]. This lack of cross-domain generalisation limits the widespread use of deep learning planning-planning algorithms.

5.4 Security and Interpretability Issues

The safety and interpretability of path-planning algorithms are crucial in path-planning tasks, especially in high-risk domains such as autonomous driving and UAVs. These issues are exacerbated by the "black-box" nature of deep learning methods.

5.4.1 Security issues.
Deep learning models may lead to erratic or even dangerous robot behaviour due to biases in the training data or limitations of the model itself. Especially in emergencies, robots may make decisions that do not meet safety requirements, posing potential risks.

5.4.2 Interpretability issues.
The decision-making process of deep learning models is usually opaque and lacks sufficient interpretability. In practice, the lack of understanding of path planning decisions may lead to algorithms that are difficult to subject to validation and revision, increasing the complexity of system design [12].

5.5 Data Issues

Deep learning models require large amounts of data for training, but the data problem remains a pressing challenge in the field of path planning.

Quality and diversity of data: in the training process of path planning, the quality and diversity of environmental data have an important impact on the training effect of the model. If the training data does not fully cover all possible obstacle configurations and environmental changes, the generalisation ability of the model will be affected [13].

The problem of labelling data: Deep learning models require a large amount of well-labelled data for training, however, data labelling is labour-intensive and in some complex environments, the amount of work involved in labelling data is huge and difficult.

6 Outlook for Future Research

Despite the many advances that have been made in deep learning for path planning, there are still many technical bottlenecks that need to be addressed to achieve wider practical applications. The following are a few possible future research directions in the area of deep learning path planning.

6.1 Cross-domain Generalisation and Adaptive Capabilities

An important challenge of deep learning in path planning is the generalisation ability of the model. In practical applications, robots often need to perform path planning in different environments and tasks. Therefore, future research should focus on improving the performance of models in cross-domain applications so that they can cope with changes in different environments and tasks.

6.1.1 Cross-domain training and transfer learning.

Through transfer learning, deep learning models can migrate knowledge from one domain to another. For example, by using simulated data from different scenarios or tasks, the robot's ability to adapt to unknown environments is enhanced.

6.1.2 Adaptive path planning.

Develop adaptive models that enable real-time adjustment of path planning strategies according to changes in the environment. In dynamic and complex environments, the robot can adjust its path based on sensor inputs and real-time data to ensure efficient and safe planning results.

6.2 Combining Traditional Path Planning with Deep Learning

Although deep learning methods have achieved good results in path planning, their high computational overhead and long training cycles limit the breadth of practical applications. Therefore, combining traditional path-planning algorithms with deep learning may be a major research direction in the future.

6.2.1 Integration of deep learning with classical algorithms.

Future research could explore how to combine deep learning with classical path planning algorithms (e.g., A*, RRT, D*) to take advantage of both. Deep learning is used to enhance the global search capability and adaptive ability of classical algorithms, while the determinism of classical algorithms is used to improve the accuracy and real-time performance of path planning.

6.2.2 Online learning and real-time path planning.

In mobile robot path planning, it is crucial to be able to make real-time learning and decisions. Combining online learning with traditional path-planning methods allows robots to learn and optimise while performing tasks, leading to better performance in dynamic environments.

6.3 Improving the Computational Efficiency and Real-time Performance of the Model

To meet the real-time demand in practical applications, improving the computational efficiency of deep learning models is another important direction for future research.

6.3.1 Lightweight modelling.

Current deep learning models tend to have many parameters and computational requirements, which is a limitation for real-time path planning tasks. Future research can be devoted to designing lightweight deep learning models to reduce computational resource consumption and improve the real-time responsiveness of path planning.

6.3.2 Edge computing and distributed learning.

Edge computing can move computational tasks from the cloud to the robot's local device, thus improving the responsiveness and robustness of the system. With edge computing and distributed deep learning, multiple robots can work together to optimise the overall path-planning performance.

6.4 Security and Interpretability

In path planning tasks in complex environments, especially high-risk tasks such as autonomous driving and UAV navigation, the safety and interpretability of robot behaviours are crucial. Therefore, future research will focus more on how to improve the safety and interpretability of deep learning models.

6.4.1 Safe path planning.

Future research could focus on how to enable deep learning models to make safe path planning decisions in high-risk environments. Safety constraints (e.g., obstacle avoidance, safe distance, etc.) in reinforcement learning can be combined to ensure the safety of the robot when performing path planning.

6.4.2 Interpretable deep learning models.

To make deep learning models more acceptable and verifiable in practical applications, the study of interpretable path planning models will become a major direction in the future. By designing interpretable deep neural networks, the robots will be able to provide comprehensibility of path planning decisions, thus enhancing the reliability and trust of the system [13].

6.5 Multimodal Sensing and Cooperative Path Planning

With the development of perception technology, future robots will be able to fuse data from multiple sensors, such as LIDAR, camera, radar, etc. Multimodal perception and collaborative path planning will become a new direction in the field of deep learning path planning.

6.5.1 Multimodal perception fusion.

By fusing data from different sensors, robots can obtain more accurate information about the environment, which in turn improves the effectiveness of path planning. Investigating how to efficiently fuse different modal information such as image data, depth data, LiDAR data, etc. will help to improve the path planning capability of deep learning models.

6.5.2 Multi-robot collaborative path planning.

With the increasing application of multi-robot systems, how to achieve collaborative path planning among multiple robots has become an important issue. Through deep learning methods, each robot can share information and optimise global path planning to avoid conflicts and improve the efficiency of task execution.

6.6 Combination of Reinforcement Learning and Unsupervised Learning

Although the application of RL in path planning has made significant progress, it still faces problems such as low data efficiency and slow convergence in the training process. Unsupervised learning, as a technique capable of training with unlabelled data, can be combined with reinforcement learning in the future to further improve the efficiency and effectiveness of path-planning algorithms.

6.6.1 Unsupervised learning combined with reinforcement learning.

In the future, it could be investigated how to combine unsupervised learning with reinforcement learning by using unsupervised learning to pre-train models, thus improving the training efficiency and data utilisation of reinforcement learning. This combination could accelerate the training process of path-planning models and allow for more efficient learning in unknown or changing environments.

6.6.2 Learning with fewer samples.

The sample-less learning technique will help to improve the learning ability of the model on small datasets. In path planning tasks, with less sample learning, robots can quickly adapt to new environments with insufficient data, especially for those scenarios that require fast response and scarce data.

7 Conclusion

This paper compares the key performance of traditional path planning algorithms and deep learning path planning by reviewing literature and other methods, studying the progress of existing applications of deep learning path planning, and putting forward many current challenges and future technology outlooks, to provide researchers with references and research ideas. In the past few years, the application of deep learning in path planning, especially methods such as deep reinforcement learning, imitation learning, and deep neural networks, has achieved significant results in tasks such as dynamic obstacle avoidance and navigation in complex environments. With the improvement of computational power, deep learning methods gradually show greater adaptability and flexibility than traditional path planning methods, especially when facing uncertain and complex environments, and can self-learn and optimise path planning strategies. At the same time, the combination of classical path planning algorithms and deep learning methods can not only improve the planning efficiency but also enhance the stability and real-time performance of the system.

However, despite the many achievements, deep learning in path planning still faces challenges such as high-state space processing, real-time requirements, environment change adaptation, and model interpretability. Future research should focus on the following directions: first, to improve the adaptability and performance of deep learning models in different environments through migration learning and adaptive path planning; second, to explore the integration of deep learning and traditional path planning algorithms to give full play to their respective advantages; third, to work on improving the computational efficiency of the models, and to push forward the application of edge computing and distributed learning techniques; fourth, to strengthen the research on path planning model security and interpretability to ensure that the system can reliably carry out high-risk tasks; and fifth, focusing on new research directions such as multimodal perception and multi-robot collaboration to provide solutions for future complex tasks and path planning in dynamic environments.

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