



Machine Learning-Based Motion Planning for Robots

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Abstract. Motion planning for robots is a crucial technology that enables autonomous navigation and the performance of complex tasks. Traditional methods have problems like low efficiency and poor adaptability in high-dimensional spaces and dynamic environments. In recent years, machine learning methods, including supervised learning, reinforcement learning, and unsupervised learning, have offered new approaches to planning robot movement. This paper conducts a systematic review of the literature. It analyzes the latest progress in using machine learning for robot motion planning. It examines the types of algorithms, their applications, and the technical challenges they present. The research focuses on combining deep reinforcement learning, supervised learning, and traditional planning methods. It investigates how these can be used in mobile robots, robotic arms, and self-driving vehicles. The paper evaluates the effectiveness of various techniques. It highlights issues such as high computational complexity, over-reliance on data, and safety concerns. It also suggests future research, such as developing lighter models and utilizing formal verification. This review aims to provide a comprehensive reference for research in the field of automation and offer theoretical support for practical applications.

Keywords: Robot motion planning, Combining machine learning, Deep reinforcement learning, Hybrid approaches, Safety issues

1 Introduction

Robotic motion planning is a key technology for autonomous driving and performing complex tasks [1]. It is widely used in industrial manufacturing, medical applications, service robots, and autonomous vehicles. However, traditional motion planning methods are increasingly limited when faced with high-dimensional spaces, dynamic obstacles, and uncertain environments [2-4]. For example, classical algorithms such as A*, Rapidly-Exploring Random Trees (RRT), and Probabilistic Roadmaps (PRM) heavily rely on accurate environmental models and fixed search methods [3]. This causes the computational complexity to rise quickly as the state space dimensions increase. In complex settings, robots often need to replan their paths. This reduces execution efficiency and limits the system's real-time ability and adaptability to the environment [5]. At the same time, in the real world, there is a lack of data and noise interference. This makes traditional methods perform poorly when dealing with

highly changeable and multi-constraint tasks. It significantly impacts the use of robotics in critical situations, such as multi-robot cooperation and self-driving [6].

In recent years, machine learning has been increasingly utilized in motion planning to address these problems. This has made traditional methods more flexible. By using data-driven pattern recognition and generalization skills, machine learning significantly enhances the efficiency and adaptability of motion planning [7]. Combining machine learning with traditional structured search methods helps solve the static problems of regular planning in changing settings. It also reduces the need for extensive labeled data. This combination enhances path planning and makes it more adaptable. It also enhances the system's autonomy and improves its security. On devices with limited resources, machine learning reduces the amount of computing needed. This enables robots to respond to environmental changes promptly and perform complex tasks [8].

Looking back at its development, robotic motion planning originated with manually designed algorithms and classic methods that employed graph search and sampling techniques. Then, machine learning and deep learning models began to be incorporated gradually. Initially, machine learning applications primarily focused on adjusting parameters and making incremental improvements [9]. However, in recent years, methods such as deep reinforcement learning and imitation learning have been increasingly used for creating and improving paths. They can quickly reach a result and plan well in changing, unpredictable environments. This trend shows that combining machine learning with traditional methods is becoming a main direction in robotic motion planning [10,11].

This paper reviews past research and then carefully examines the integration of machine learning with traditional motion planning methods. It focuses on real-world applications in mobile robots, robotic arm control, and autonomous vehicles, such as self-driving cars. Additionally, the paper will evaluate the performance of various techniques. It will summarize the current problems and explore possible future trends, like combining lightweight models with formal verification. This paper uses a structured method. Its goal is to provide researchers with a full-scale reference. This helps to advance the theoretical study and real-world use of robotic motion planning.

2 Methods to Combine Machine Learning and Traditional Robot Motion Planning

The basic principle of robot motion planning is to create collision-free paths from a start point to a target point using models of the environment. For example, use occupancy grids or configuration spaces [12]. At the same time, optimize constraints like making the path shorter, reducing time, or using less energy. The primary components of robotic motion planning include state space representation, obstacle detection, and path search. This process involves converting the real-world space into numbers and sections, and then mapping it to a virtual space. After that, a computational search is used to find possible paths. The goal is to strike a balance

between the speed of real-time processing and the quality of the path. Finally, the final path is created [13].

Traditional robot motion planning methods, such as A*, Rapidly-Exploring Random Trees (RRT), and Probabilistic Roadmaps (PRM), can work efficiently and accurately in certain dynamic and high-dimensional situations when utilizing specialized algorithms [14-16]. But they have problems. The computational complexity is high, and adaptability is poor in complex, dynamic environments. Machine learning employs a data-driven approach to education. It can be combined with traditional methods and has excellent potential. This combination combines structured search with adaptable features, enhancing overall performance. The following sections examine methods for integrating robot motion planning with machine learning. These methods center on adjusting parameters, optimizing paths, and integrating frameworks. Many studies have proven their effectiveness [14].

2.1 Integration of Parameter Optimization

Parameter optimization fusion utilizes machine learning to dynamically adjust the parameters of traditional planning algorithms, enabling them to adapt to environmental changes. For example, reinforcement learning (RL) methods can improve the sampling strategy of Rapidly-exploring Random Trees (RRTs) [17]. They do this by making cumulative rewards as big as possible. This highlights the importance of good paths and helps address the issue of random sampling being inefficient. Similarly, supervised learning can utilize existing data to train models and continually refine function parameters. This method retains the certainty of traditional algorithms while incorporating machine learning's ability to adapt. It enables algorithms to work more effectively in dynamic situations [17].

2.2 Fusion of Path Generation and Optimization

Path generation and optimization fusion means using traditional methods to make a rough initial path in path planning. Then, machine learning is used to improve and adjust this path. For instance, RRT can quickly create workable paths. On the other hand, imitation learning methods enhance the smoothness of the trajectory and the ability to avoid obstacles once the task begins. This combination significantly reduces the need for replanning and enhances computational efficiency in dynamic situations. Research shows this multi-layer approach cuts planning time by more than 30% and has higher success rates [18].

2.3 Integration and Fusion of Data-Driven Framework

Data-driven framework integration fusion works as follows: First, traditional methods are used to generate training data through simulation. Then, train machine-learning models to learn strategies from this data. This way, a closed-loop system is formed. For example, unsupervised learning is used to lower the number of dimensions in high-dimensional state spaces [19]. This helps traditional PRM build roadmaps. After that, reinforcement learning enhances the entire framework by utilizing feedback from repeated interactions. This method reduces the need for computational resources. It's perfect for embedded systems with limited resources. Also, it can quickly adjust to new situations using transfer learning [19].

These fusion methods combine the best aspects of both approaches to achieve optimal results. They address the fixed problems of old-style planning, reducing data needs and training requirements for machine learning. This offers strong support for more complicated robot applications.

3 Practical Uses of Hybrid Methods in Common Situations

Combining machine learning with traditional motion planning methods has demonstrated superior performance compared to using these techniques alone in real-world applications. These hybrid methods use data-driven learning and structured search algorithms. This helps them plan paths more efficiently and reliably in complex, changing environments. Each field has developed its own unique methods for combining elements and technical approaches tailored to specific application areas and technical features. This analysis examines three everyday use cases: mobile robot navigation, robotic arm operation, and autonomous driving.

3.1 Mobile Robot Navigation's Fusion Applications

Fusion methods are widely used in mobile robot navigation. Real-time obstacle avoidance and path optimization in 3D dynamic environments have long been significant challenges, preventing mobile robots from being widely utilized. Combining data from multiple sensors enables mobile robots to navigate more effectively. When data from sensors such as LiDAR, cameras, and IMUs are combined, the system can create more accurate models of the environment. In this step, deep-learning networks, such as convolutional neural networks (CNNs), play a significant role in information processing [20]. Traditional probabilistic filtering methods are used for sensor data fusion. This fusion design demonstrates excellent navigation capabilities in both indoor and outdoor complex environments. Combining reinforcement learning and artificial potential field methods is another important research area. Robots can use the potential energy of artificial potential fields as rewards for reinforcement learning. This helps them avoid obstacles and reach targets more efficiently. This approach enables deep reinforcement learning networks to converge more effectively.

3.2 Fusion Methods for Robotic Arm Operation

In robotic arm task planning, fusion methods are mainly used for trajectory optimization and skill learning. By combining traditional kinematic and dynamic constraints with machine-learning adaptive learning, practical solutions for complex manipulation tasks can be found.

In creating and refining movement paths, this paper can combine supervised learning with traditional inverse kinematics methods. This paper collects data from expert examples. Then, supervised learning models figure out how task goals lead to joint angle sequences. Meanwhile, traditional kinematic rules make sure the generated paths are physically possible. This fusion method is particularly effective in industrial grasping and assembly tasks. By replicating human hand movements repeatedly, robot arms can significantly reduce planning time while maintaining accuracy [21].

Combining imitation learning and reinforcement learning enables robotic arms to transfer skills effectively. First, imitation learning gets basic strategies from human demonstrations. Once enough learning progress is made, reinforcement learning is used to adjust and improve strategies in new environments. This two-stage fusion method addresses the inefficiency of reinforcement learning that often starts from a blank slate. At the same time, it keeps the robotic arm's ability to adapt to new tasks.

3.3 Fusion at Multiple Levels in Self-Driving Cars

Planning the path for self-driving cars is the most complex situation for fusion methods. Rules of the road, dynamic obstacles, ensuring passenger comfort, and safety are significant challenges associated with the use of this technology. A multi-level fusion architecture offers a novel approach to addressing these complex issues.

In autonomous driving, fusing behavior prediction and trajectory planning is a key technology. Onboard computer systems can utilize long short-term memory (LSTM) networks to predict the intentions of other vehicles. They combine this with traditional safe trajectory generation optimization algorithms. This way, in multi-vehicle interaction scenarios, they can carry out safe and efficient lane changes and overtaking. Research shows that this combined method boosts success rates by approximately 40% in challenging traffic situations, outperforming rule-based methods.

Combining visual-language multimodal models with traditional planning methods creates new opportunities for human-machine interaction in vehicle control. Autonomous systems can understand complex spoken commands by combining the reasoning skills of large language models with the accuracy of regular planning algorithms. Then they can send these commands to traditional planning algorithms to create driving paths. This multimodal fusion approach is still new. It creates new ways for autonomous driving that's driven by human-machine interaction.

4 Challenges and Future Research Areas

Integrating machine learning with traditional robotic motion planning has broad technical prospects. However, it has several problems, including limited computational resources, difficult-to-access data, and system security issues. These limitations significantly hinder further technological use. Solving them is an important area for future research. This section will outline three primary topics one by one: computational difficulty, data reliance, and security. It will also outline related avenues for future research.

4.1 Computational Difficulty

Traditional planning algorithms, such as the RRT, have exponential complexity in their sampling process. Adding deep reinforcement learning or neural networks makes the computational load even greater. Training and inferring with more complex models require a significant amount of GPU resources. This not only makes the computation slow, causing increased latency and energy consumption, but also makes

the computational units significantly larger, making deployment more challenging. For example, in multi-robot teamwork situations, each step of optimization in a fusion system may require several seconds to complete. This is a delay that can't be accepted for tasks where robots need to work together in sync. Moreover, in dynamic environments, often having to replan exacerbates this problem. It might lead to system overload or paths that are not continuous.

Future research primarily focuses on developing efficient and lightweight models to address computational complexity. Techniques such as neural network pruning, quantization, and knowledge distillation can reduce the parameter size of fusion frameworks by over 50% while maintaining accuracy. Latest studies on data-driven motion planning demonstrate that simple DRL types, combined with traditional sampling methods, can achieve millisecond-level inference on embedded systems. Additionally, utilizing distributed machine-learning techniques, such as federated learning or edge computing setups, can distribute the computing workload across multiple devices. This can significantly reduce the computing problems on single nodes.

4.2 Data Dependency

Data dependency problems come from machine learning needing large amounts of high-quality training data. Robotic motion planning also has this same problem. Fusion methods require simulating or collecting a vast amount of data on environmental interactions. Models that work better and can be used in more situations require even larger and higher-quality training datasets. But in the real world, there are problems. The necessary data for this paper may be of poor quality or scarce. It can also be expensive to label the data. Noise, like sensor errors in measurement and recording, can also be an issue. These things can make the final model less accurate. This challenge makes training cycles longer and stops personalized use. For example, it makes it challenging for mobile robots to operate on various terrains.

In the future, research will focus on combining generative AI and transfer learning more deeply. Generative AI can quickly make fake data. Transfer learning methods can utilize this data to accelerate cross-domain adaptation. Generative AI models, such as GANs or diffusion models, can soon generate a large amount of realistic fake data. This can help when there isn't enough real-world data. Using transfer learning methods, such as domain adaptation, knowledge can be quickly transferred from the source domain to the target domain. Additionally, utilizing meta-learning frameworks enables models to converge rapidly in few-shot scenarios. Future growth of multimodal models may use this method to generate multimodal data.

4.3 Safety

Safety is the most important thing for any planning technology. However, current machine-learning systems employ black-box decision-making methods. These methods can pose safety risks, such as unexpected collisions or system failures. This problem is particularly severe in human-machine coexistence situations, such as self-driving cars or medical robots. Also, there are potential risks such as malicious attacks and conflicts among multiple agents. For example, a recent report on

deep-learning path planning stated that insufficient robot safety is the primary issue for real-world use, particularly in high-risk areas such as surgical robotics.

In future research, making formal verification and multi-agent assurance mechanisms deeper could be very important. Formal verification employs mathematical methods, such as proofs and game theory, to ensure that strategies are reliable and effective. For example, use integrated model-checking tools to verify that RL strategies remain stable in the face of potential attacks. Additionally, utilize game theory frameworks to determine safety limits in interactions among multiple robots. Future development areas include explainable AI technologies. For example, utilize attention mechanisms to demonstrate how AI makes decisions and mitigate "black box" problems.

5 Conclusions

This paper demonstrates how machine learning is systematically integrated with robotic motion planning. It covers principles, methods, applications, evaluations, challenges, and future directions. This fusion transcends the static limitations of traditional techniques and the computational bottlenecks of machine learning. It offers benefits in terms of efficiency, adaptability, and safety in practical situations.

However, there are still some long-lasting problems. These include complex, high-dimensional situations; real-time operation in uncertain settings; few rewards; imbalances in deep reinforcement learning; rewards that are too sensitive; high memory usage; insufficient validation; and differences between simulation and real-world applications. Other challenges include coordinating multiple robots to work together, scaling the system to a larger scale, and ensuring safe interactions between humans and robots. This is especially crucial in high-risk areas, such as autonomous vehicles and medical robots.

In the future, this paper should utilize advanced AI for flexibility, meta-learning for generalization, quantum computing for high-dimensional tasks, lightweight hybrid systems, and ethical human-robot collaboration to address these problems. Some good areas are making deep reinforcement learning more efficient, reducing the gap between simulation and reality, and applying it to multi-agent dynamic environments. Utilizing machine learning to enhance sampling-based planners can help prevent collisions and improve key metrics, including path length and energy.

Ultimately, this approach enables robots to make informed decisions. As new technologies solve problems, they promote sustainable automation with great potential.

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