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Progress in the Application of Deep Reinforcement Learning in Path Planning and Control of Mobile Robots

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Abstract:

This study reviews the progress in the application of deep reinforcement learning in the field of path planning and control for mobile robots. Traditional methods exhibit poor adaptability in complex and dynamic environments, struggling to handle static and dynamic obstacles as well as environmental uncertainties. Deep reinforcement learning enables robots to autonomously interact with the environment and learn optimal strategies, significantly enhancing the performance of path planning and control. The article provides a detailed analysis of the limitations of traditional methods, such as high computational complexity, susceptibility to local optima, and lack of adaptability. It also introduces the advantages of deep reinforcement learning algorithms (e.g., DDPG, SAC) and their improved variants (e.g., APF-DDPG, AM-LSTM-SAC). These algorithms demonstrate excellent experimental results in various environments through multi-algorithm fusion strategies. The paper further discusses the setup of simulation environments, experimental configurations, and result analysis, summarizing existing achievements and shortcomings while providing an outlook on future research directions. This work offers valuable insights for the further development of mobile robot technology.

Keywords: Deep reinforcement learning, Mobile robots, Path planning, Control, DDPG, SAC

1. Introduction

With the rapid development of artificial intelligence and automation technologies, mobile robots are increasingly being applied in various fields such as industrial manufacturing, logistics and distribution, medical services, and home assistance. In industrial manufacturing, mobile robots can undertake tasks such as material handling and assembly; in logistics, they enable efficient transportation and sorting of goods; in medical services, they assist healthcare workers in delivering medications and transporting equipment; and in home assistance scenarios, they perform tasks like cleaning and security patrols. In these applications, path planning and control are core technologies that ensure the efficient and safe operation of mobile robots. Traditional path planning and control methods often exhibit poor adaptability and flexibility in complex and dynamic environments. For example, in complex factory environments, traditional methods may fail to promptly respond to the appearance of dynamic obstacles, leading to path planning failures. In logistics warehouses, faced with large quantities of goods and frequently changing layouts, it is challenging to quickly find optimal paths. The emergence of deep reinforcement learning offers new opportunities to address these issues. By enabling robots to autonomously learn optimal strategies through interaction with the environment, deep reinforcement learning allows robots to better adapt to complex environments and improve path planning and control performance. This study provides a systematic review and analysis of the application of deep reinforcement learning in path planning and control for mobile robots.

2. Challenges in Path Planning and Control for Mobile Robots

In real-world scenarios, mobile robots face complex and diverse environmental conditions, with obstacles appearing in various forms. Static obstacles, such as buildings and furniture, and dynamic obstacles, such as pedestrians and vehicles, collectively create a complex obstacle environment. The distribution of these obstacles in space is irregular, and their motion states are highly random and uncertain, significantly increasing the difficulty of path planning. Additionally, there are numerous challenges in acquiring and processing environmental information. Sensors often produce measurement errors, and data noise is unavoidable. These factors can lead to deviations in the robot's perception of its surroundings, adversely affecting path planning and control decisions, thereby increasing the risks and challenges during task execution.

Traditional path planning methods, such as the classic A* algorithm and Dijkstra algorithm, exhibit significant limitations in complex environments [1,2]. Their computational complexity increases sharply with environmental complexity, requiring substantial computational resources and time to find feasible paths in large-scale maps or environments with numerous complex obstacles. More critically, these algorithms are prone to falling into local optima, making it difficult to find globally optimal paths, and often resulting in planning outcomes that fail to meet practical requirements. Rule-based control methods, due to their inherent rigidity and limitations, struggle to cope with dynamic environmental changes. They lack the ability to autonomously adjust strategies based on real-time environmental changes, making them ineffective in handling situations such as the sudden appearance of obstacles or abrupt changes in environmental layouts. In complex and dynamic real-world scenarios, these traditional methods fall short of meeting the application requirements of mobile robots, severely limiting their performance and application scope.

3. Application of Deep Reinforcement Learning in Path Planning for Mobile Robots

3.1 Improvements Based on the DDPG Algorithm

3.1.1 APF-DDPG Algorithm

In mobile robot collision avoidance planning tasks, the traditional DDPG algorithm suffers from slow convergence, significantly impacting its application effectiveness. Researchers such as Wang Xiaoning[3] innovatively proposed the APF-DDPG algorithm, providing a new approach to address this issue. This algorithm ingeniously incorporates the Artificial Potential Field (APF) method to adjust the robot's angular velocity. In the early stages of training, this improvement effectively guides the robot to reach the target point more quickly while enabling it to master collision avoidance strategies faster. Through extensive experiments conducted in a Gazebo simulator based on ROS, which includes environments with no obstacles, static obstacles, and dynamic obstacles, the results show that the APF-DDPG algorithm significantly improves convergence speed and achieves higher average rewards compared to the traditional DDPG algorithm in various scenarios. This allows the robot to complete collision avoidance planning tasks more efficiently, demonstrating the algorithm's effectiveness and superiority.

3.1.2 APF-SPER-DDPG Algorithm

To further address the bottlenecks of low sample utilization and path redundancy in the DDPG algorithm, the APF-SPER-DDPG[3] algorithm was developed. The core innovation of this algorithm lies in the introduction of the Prioritized Experience Replay (SPER) mechanism and the use of a "Sum-Tree" data storage architecture. This approach enables the algorithm to utilize sample data more efficiently during operation, significantly improving its runtime efficiency and sample utilization. Additionally, the algorithm employs multi-step expected temporal difference methods to solve for optimal policies, further accelerating convergence. In simulation experiments involv-

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ing diverse static and dynamic obstacle environments, the APF-SPER-DDPG algorithm was comprehensively compared with the APF-DDPG algorithm. The results indicate that the new algorithm demonstrates clear advantages in key metrics such as convergence speed, training duration, and collision avoidance planning performance, making it more effective in handling collision avoidance tasks in complex environments and providing more reliable safety guarantees for mobile robots.

3.2 Improvements Based on the SAC Algorithm

Given that the DDPG algorithm's deterministic policy limits its exploratory capabilities and adaptability in complex environments, some researchers have turned their attention to the SAC algorithm and made significant improvements. Wang Xiaoning[3] and colleagues designed the AM-LSTM-SAC algorithm, a representative example of such improvements. This algorithm innovatively integrates Long Short-Term Memory (LSTM) networks into the SAC algorithm, greatly enhancing its ability to learn from sequential sample data and effectively addressing the issue of insufficient representation of obstacle state information in DDPG-based collision avoidance planning methods.

Furthermore, the algorithm optimizes LSTM encoding using attention-based mechanisms, further improving data quality and enabling the algorithm to more accurately capture environmental information during the learning process, thereby accelerating convergence. In simulation experiments across different obstacle environments, the AM-LSTM-SAC algorithm was compared with the APF-SPER-DDPG algorithm and the traditional SAC algorithm. The results show that the AM-LSTM-SAC algorithm outperforms in key aspects such as path length, smoothness, and collision avoidance success rate, demonstrating excellent stability and strong generalization capabilities. This provides a more effective solution for path planning in complex environments.

4. Application of Deep Reinforcement Learning in Mobile Robot Control

4.1 Control Methods Based on Deep Reinforcement Learning

For mobile robot control, a trajectory tracking human-like intelligent control method based on deep reinforcement learning has been developed. The design of the underlying controller incorporates human-like intelligent control principles, achieving an organic integration of perception schemas, motion schemas, and control coordination. By real-time monitoring and analysis of the robot's pose error states, characteristic modes are accurately determined, and appropriate control modes are selected accordingly.

In the application of deep reinforcement learning, its advantage in adjusting control parameters under small error states is fully utilized. With specially designed modules for extracting motor operating characteristics and calculating velocity vector errors, comprehensive information about the robot's operating state is obtained. During the robot's trajectory tracking process, deep reinforcement learning continuously optimizes control strategies through extensive training and trial-and-error, gradually obtaining optimal control parameters. This approach successfully achieves high-precision trajectory tracking control for three-wheeled omnidirectional mobile robots[4], significantly enhancing the robot's motion control performance in complex environments and enabling more stable and accurate movement along predefined trajectories.

5. Research Summary and Outlook

5.1 Summary of Research Achievements

In the research progress of path planning and control for mobile robots, existing studies have achieved a series of key advancements through continuous improvement and innovation of deep reinforcement learning algorithms. Numerous carefully refined algorithms have demonstrated significantly enhanced capabilities in addressing the challenges of complex and dynamic environments. In terms of path planning efficiency, innovative strategies such as integrating ant colony algorithms with deep reinforcement learning have effectively improved planning speed and accuracy, enabling robots to quickly and precisely plan reasonable paths while skillfully avoiding various static and dynamic obstacles. This greatly reduces travel time and energy consumption. In terms of control precision, improvements such as optimizing network structures and reward mechanisms have made the robot's motion control more accurate and stable, allowing it to closely follow predefined trajectories with reduced deviations and jitter. These achievements provide a solid technical foundation for the widespread application of mobile robots in real-world scenarios, significantly expanding their application depth and breadth, and strongly advancing the development of mobile robot technology.

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