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Research on Robot Navigation Algorithms Based on Machine Learning

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Abstract. Robot navigation constitutes one of the core challenges in the field of intelligent robotics. Path planning algorithms are designed to generate the complete movement trajectory of a robot, enabling it to reach the target destination from its initial position rapidly, efficiently, and safely. Traditional path planning algorithms can achieve path planning to a certain extent, but in complex task spaces with dynamic obstacles, numerous issues emerge, and task completion demands substantial computational resources. In recent years, with the rapid advancement of machine learning, researchers have investigated intelligent path planning algorithms from the perspective of algorithmic characteristics to enhance their intelligence. This paper examines the current development status of machine learning-aided path planning algorithms through a comprehensive. It focuses on the critical role of various reinforcement learning approaches in autonomous navigation, and analyzes existing challenges and development trends. It concludes that deep reinforcement learning is more suitable for navigation tasks, thereby providing a reference for subsequent practical applications of navigation systems.

Keywords: Robot, Autonomous Navigation, Machine Learning, Path Planning, Reinforcement Learning

1. Introduction

With the rapid advancement of artificial intelligence and robotics, robot navigation has emerged as a pivotal research direction in contemporary times. Navigation technology serves as the foundation for robots to accomplish diverse complex tasks, enabling them to plan motion trajectories and reach the target destination from the initial position quickly, efficiently, and safely [1]. Path planning algorithms find extensive applications in scientific research, industrial settings, and daily life scenarios. Currently, path planning algorithms can be categorized into two categories according to their characteristics and key technologies: conventional methods and reinforcement learning-based methods [2]. Traditional path planning algorithms such as A* and Simultaneous Localization and Mapping, are applicable to route finding of autonomous vehicles, trajectory generation in simulation environments, and navigation for logistics robots. However, when applied to complex task spaces with dynamic obstacles, traditional algorithms exhibit numerous limitations, as task completion requires significant computational costs. To address this issue, scientists have integrated machine

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learning with navigation algorithms, enabling robots to achieve autonomous navigation in complex environments.

This paper explores the rapid development of machine learning-aided path planning algorithms through a systematic literature review and case analysis. It focuses on reinforcement learning-based path planning technologies, encompassing value-based and policy-based approaches. It further introduces deep reinforcement learning, hierarchical reinforcement learning, multi-agent reinforcement learning, and the integration of machine learning with traditional planning algorithms. It analyzes existing challenges and development trends, providing a reference for the future applications of autonomous navigation.

2. Theoretical overview

2.1. Robot navigation

Artificial intelligence algorithms for autonomous robot navigation comprise classical methods, machine learning approaches, and deep learning techniques. Robot navigation typically involves four fundamental stages: perception, localization and mapping, path planning, and motion control. In the context of path planning, it can be classified into global path planning and local path planning [3].

Global path planning involves selecting a complete path based on a known environmental map. Common methods include A*, Ant Colony Optimization, and RRT [4]. Since these algorithms rely on known static map information, they are challenging to apply in dynamic environments. Local path planning methods, such as the Dynamic Window Approach, are used to handle dynamic environmental changes and re-plan local paths. While these methods exhibit high computational efficiency, they are prone to becoming trapped in local optima.

Among classical algorithms, Dijkstra's algorithm explores nodes systematically from the starting point in ascending order of cost, thereby ensuring the discovery of the optimal path. However, due to its adoption of an omnidirectional expansion strategy, this algorithm frequently traverses a large number of redundant nodes in complex environments, leading to substantial computational costs. In contrast, A* introduces a heuristic function that estimates the actual cost from the current node to the target node. This heuristic guidance mechanism allows the search process to more efficiently lock onto the target, thereby reducing node expansion and computation time.

Traditional navigation frameworks utilize the SLAM algorithm to construct maps of unknown environments and subsequently employ localization algorithms to determine the robot's current position and movement state. These frameworks can be categorized into visual SLAM and laser SLAM [5]. However, the constrction and updating of obstacle maps are time-consuming and necessitate dense high-precision sensors. Consequently, traditional navigation algorithms face challenges in practical applications and often lead to errors due to heavy computational loads.

2.2. Fundamentals of machine learning

Machine learning refers to the process through which a computer program learns from experience to enhance its performance on a specific task. Machine learning algorithms are generally divided into three categories: supervised learning, unsupervised learning, and reinforcement learning [6]. Supervised learning algorithms are grounded in inductive reasoning, in which models are trained using labeled data to conduct classification or regression tasks. Unsupervised learning encompasses techniques such as density estimation and clustering, which are applied to unlabeled data. The

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objective of reinforcement learning is to maximize the rewards an agent can obtain in a complex and uncertain environment. By perceiving the environmental state and responding with actions, the agent is guided to select more optimal actions to achieve the maximum reward. This process is referred to as learning through interaction or learning from trial and error. A key challenge in contemporary reinforcement learning is managing the trade-off between exploration and exploitation.

3. Research on robot navigation algorithms based on machine learning

Traditional model-based navigation algorithms are constrained in dynamic environments and under complex constraints. In contrast, machine learning enables the learning of optimal strategies through interaction with the environment. Furthermore, machine learning equips robots with end-to-end perception and adaptive decision-making capabilities, thereby laying the foundation for autonomous navigation applications. This chapter systematically explores the research progress and practical applications of machine learning-based robot navigation from four perspectives: supervised and unsupervised learning approaches, reinforcement learning and deep reinforcement learning, hierarchical, multi-agent, multi-objective reinforcement learning, and the integration of machine learning with traditional navigation algorithms.

3.1. Supervised and unsupervised learning methods

In the field of robot navigation, supervised and unsupervised learning are primarily applied in key areas such as perception modeling, path prediction, and environmental feature extraction, thereby playing an auxiliary role in robot navigation systems [6]. Supervised learning leverages labeled training sets provided by external supervisors and adopts a task-driven framework. Visual navigation models based on Convolutional Neural Networks can directly map camera images to control commands, realizing “end-to-end” path prediction and obstacle avoidance decision-making. Additionally, they are also applied to trajectory regression and path imitation, predicting continuous action sequences via deep regression networks to learn and imitate the correct navigation path. For instance, MPNet achieves path planning in both visible and invisible environments via a near-optimal heuristic function learned by a neural network [7].

Unsupervised learning is a typical process for discovering hidden structures in unlabeled data and adopts a data-driven framework. Such methods facilitate the extraction of scene structural information, improve the global consistency of path planning, provide environmental representations and data for navigation algorithms, and enhance the efficiency of path planning.

3.2. Reinforcement learning and deep reinforcement learning

Reinforcement learning has become an important tool for addressing continuous control and planning problems and it can learn complex strategies in high-dimensional environments. Unlike supervised learning, RL takes the Markov Decision Process into account and does not depend on external labels; instead, it autonomously explores optimal strategies through a “trial-and-error” mechanism. Its core comprises five fundamental elements: environment, agent, state, action, and reward. The agent perceives the environmental state, executes actions, and continuously optimizes its decision-making strategy based on reward feedback, thereby achieving autonomous learning and navigation through interaction with the environment.

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Reinforcement learning algorithms are primarily categorized into value-based and policy-based methods. Value-based methods, such as Q-learning, learn optimal strategies by estimating the expected return of state–action pairs. However, when the state and action space are high-dimensional and continuous, the Q-table becomes impractical. Consequently, the Deep Q-Network was proposed, which uses neural networks to approximate Q-values and incorporates experience replay and fixed Q-targets to enhance performance. On the other hand, policy-based methods, such as Policy Gradient, directly learn the mapping function from states to actions, making them suitable for continuous action spaces. The Actor–Critic combines the advantages of both to achieve more stable and efficient policy updates.

Traditional RL serves as the foundation of navigation intelligence; however, in high-dimensional problems, RL confronts the curse of dimensionality, in which the computational cost increases sharply with the number of input variables. Deep learning methods approximate any nonlinear function by training deep neural networks and learning the inherent laws and features of input data. DRL-based navigation systems are defined by three key elements that directly dictate their application scenarios and performance: state space S, action space A, and reward function R. DRL navigation can adapt to complex systems without requiring expert demonstrations, rendering the navigation process more intelligent. Numerous well-known DRL algorithms, such as DQN, DDPG, PPO, along with their variants, have been adapted to realize DRL navigation systems. The Asynchronous Advantage Actor–Critic algorithm reduces experience correlation and enhances training stability through multi-threaded parallel interactions with the environment. The Soft Actor–Critic (SAC) algorithm maximizes both the expected reward and policy entropy to enhance the efficiency of data utilization. The Deep Deterministic Policy Gradient (DDPG) integrates deep neural networks and deterministic policy outputs to achieve efficient single-step updates in continuous action spaces [8]. Even in dense dynamic obstacles, it can avoid short-term decisions and collisions, ensuring greater safety. In UAV navigation, DRL assits robots overcome complex wind fields and adapt to various nonlinear disturbances. Nowadays, pedestrian trajectory prediction is also used as an auxiliary training task, enabling robots to predict the next movement of obstacles while avoiding collisions.

3.3. Hierarchical reinforcement learning, multi-agent reinforcement learning, and multi-objective reinforcement learning

When applying reinforcement learning to complex real-world scenarios such as autonomous driving, traditional single-agent and single-objective models still have limitations. Researchers have proposed a range of advanced approaches to address this issue. Hierarchical Reinforcement Learning incorporates task abstraction and hierarchical decision-making mechanisms to tackle the dimensionality curse in complex tasks, reducing training duration and resource expenditure while enhancing policy generalization [9]. Multi-Agent Reinforcement Learning expands its research scope from a single agent to multiple coexisting and interacting agents. It employs the stochastic games framework for analysis and can be categorized into cooperative, competitive, or hybrid paradigms. It now enables the training of agents to exhibit human-like interaction capabilities in autonomous driving [10]. Multi-Objective Reinforcement Learning aims to resolve trade-offs among multiple conflicting objectives in real-world decision-making. Its goal is not to find a single optimal policy but a set of Pareto-optimal solutions. This enables autonomous driving systems to quantify and balance inherent conflicts such as traffic efficiency and safety, comfort, and energy consumption, providing strategies with various decision preferences.

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3.4. The combination of machine learning and traditional navigation algorithms

In overly complex environments, DRL navigation may get trapped in local optima and exhibit instability. In this case, DRL relies on supplementary global information furnished by traditional navigation techniques to form a complementary hybrid architecture. This type of navigation algorithm is the mainstream research orientation and among the most promising technical avenues in autonomous driving tasks. In practical applications, a hierarchical design is typically employed: traditional algorithms generate a globally optimal or suboptimal trajectory based on the map to ensure overall task feasibility, while the DRL agent is tasked with local trajectory tracking and dynamic obstacle avoidance, outputting precise control commands. There are now diverse integration schemes, such as combining the Soft Actor–Critic algorithm with the Hybrid A* algorithm, or utilizing DRL for policy control while leveraging SLAM for accurate localization and map construction [11]. These hybrid algorithms combine the adaptability and flexibility of DRL in handling complex scenarios with the safety of traditional methods, meeting the requirements of intelligent navigation systems.

4. Challenges and development directions

Deep learning strategies have contributed substantially to autonomous navigation and driving, enhancing safety and alleviating the workload of human operators while facilitating the recognition of lanes, vehicles, pedestrians, and traffic signs [12].

However, in practical applications, factors including the expansion of environmental scale, elevated complexity, and temporal state uncertainty must be incorporated into algorithm design. Most algorithms depend on specific training environments, and their performance degrades substantially when transferred to new scenarios, making it challenging to complete navigation tasks in complex environments. At the same time, deep reinforcement learning methods usually require extended training durations and impose stringent requirements on the efficiency of computational hardware and the lightweight design of algorithms. Navigation performance is susceptible to sensor noise and perceptual constraints, making it difficult to ensure the accuracy and consistency of environmental map construction. Endowing navigation algorithms with online learning capabilities also constitutes one of the current challenges, allowing them to adapt to new areas and changing traffic environments while mitigating catastrophic forgetting. In addition, trajectories generated by deep reinforcement learning sometimes fail to align with the actual kinematic constraints of robots.

To overcome these challenges, researchers are pursuing multiple research avenues to substantially enhance the real-time performance, completeness, and optimality of navigation algorithms. First, lifelong learning methodologies are under in-depth investigation. High-fidelity simulation environments can be leveraged to shorten the training cycle, and domain adaptation techniques can bridge the gap between virtual and real scenarios. Behavioral prediction can be integrated into algorithms to enable multimodal perception and data fusion, strengthening the modeling of environmental uncertainty. Investigating the integration of reinforcement learning with traditional methods can make navigation systems adopt more hybrid architectures that integrate the perceptual capabilities of deep learning with the interpretability and stability of traditional algorithms, thus realizing navigation systems that balance performance and safety. Finally, by analyzing the discrepancies between different navigation frameworks across various environments, the most appropriate algorithms can be selected and integrated into navigation systems to develop more intelligent navigation algorithms.

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5. Conclusion

Navigation algorithms are a major challenge faced by mobile robots. This paper systematically reviews robot navigation methods based on machine learning. At present, deep reinforcement learning has attracted widespread attention for its powerful performance and learning ability in real-world scenarios and has been applied in autonomous driving, mobile robots, and industrial robots. The integration of reinforcement learning and deep neural networks marks a major breakthrough in the field of navigation, enabling models to effectively learn the underlying features of input data and ultimately achieve autonomous navigation. Leveraging the advantages of deep neural networks can enhance robots' motion control performance and autonomous navigation stability in both static and dynamic environments.

Value-based and policy-based reinforcement learning, hierarchical reinforcement learning, and multi-agent reinforcement learning can operate without maps in different scenarios and handle the "curse of dimensionality" in high-dimensional problems. Although deep reinforcement learning has strong learning ability and low dependence on sensor accuracy, allowing it to replace the localization and mapping of traditional navigation frameworks, it is still prone to local optima in complex environments. Therefore, combining it with global traditional navigation algorithms is the mainstream research direction. At the same time, with the addition of lifelong learning and multimodal perception technologies, machine learning-based navigation algorithms will play an increasingly important role in practical applications.

However, it lacks specific algorithmic analysis and comparative results of practical applications in specific environments. Future research can further focus on particular deep reinforcement learning algorithms, exploring their applications in complex industrial environments or real navigation. In addition, in-depth research on combining navigation algorithms with other fields can improve the intelligence and adaptability of navigation systems.

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