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Automated Driving Target Detection and Path Planning Based on Deep Reinforcement Learning

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Abstract. With the rapid development of Intelligent Connected Technology, autonomous driving has become an important research direction for the future of transportation. Object detection and path planning are core tasks of autonomous driving systems. Methods based on deep reinforcement learning (DRL) possess strong optimization capabilities, demonstrating significant potential in coping with complex traffic environments. This thesis reviews the application of deep reinforcement learning in target detection and path planning for autonomous driving, with a focus on analyzing the advantages of deep reinforcement learning in enhancing target detection accuracy and handling dynamic traffic environments. It also explores its capabilities in dynamic obstacle avoidance and real-time decision-making in path planning. It addresses the challenges and limitations currently faced in the application of DRL, aiming to provide researchers with a comprehensive perspective on the current status of deep reinforcement learning in autonomous driving, the technical challenges involved, and future development directions, thereby promoting further research and application in this field.

Keywords: Deep Reinforcement Learning, Autonomous Driving, Target Detection, Path Planning.

1. Introduction

With the rapid development of Intelligent Connected Technology, autonomous driving has become an important research direction for future transportation. The autonomous driving system performs real-time target detection and path planning to autonomously complete complex driving tasks in complex traffic environments. Current autonomous driving decision-making technologies can be broadly categorized into two types: rule-based decision-making methods and learning-based decision-making methods [1]. Rule-based methods rely on a predefined rule library and are highly logical, but they have limitations when faced with complex and dynamic traffic scenarios. Learning-based decision-making methods can learn from large amounts of driving data and optimize themselves according to changing environments, demonstrating strong adaptability and flexibility. In recent years, autonomous driving decision-making methods based on deep reinforcement learning (DRL) have become an important research direction in autonomous driving as a learning-based method. Through repeated training in a simulated environment, this type of autonomous driving decision-making method can continuously optimize decision-making strategies through a process of

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trial and error, overcoming the limitations of traditional rule-based systems. With the continuous advancement of technology, autonomous driving systems based on deep reinforcement learning are expected to play a key role in improving traffic safety, efficiency, and adaptability, driving further development in the field of intelligent transportation. This paper provides an overview of the specific applications of deep reinforcement learning algorithms in the two fields of autonomous driving target detection and path planning, and analyzes the limitations of DRL algorithms in the field of autonomous driving. The aim is to help readers understand the key technologies, issues that still need to be resolved, and future development trends in this interdisciplinary field, and to provide theoretical support and technical references for subsequent research.

2. Overview of DRL

Reinforcement learning is a machine learning method that differs from supervised learning and unsupervised learning. It involves an agent interacting with an environment to obtain rewards, thereby continuously optimizing its action strategy to maximize its long-term benefits. Deep reinforcement learning combines deep learning methods and has strong abstraction and representation capabilities [2]. Below are two common deep reinforcement learning algorithms:

2.1. Deep Q network

Deep Q network (DQN) is a classic value function method that combines Q-Learning and deep learning algorithms to learn optimal strategies in complex environments [1]. In traditional Q-learning, the agent estimates the value of each state-action pair by maintaining a Q-table, but this can be impractical when the state space is too large. DQN uses deep neural networks instead of Q tables to approximate the Q-value function:

$$Q(s, a; \theta) \approx expected\ reward \tag{1}$$

DQN is suitable for discrete action spaces, such as action selection problems in autonomous driving, such as “turn left” and “brake”.

2.2. Proximal policy optimization

Proximal policy optimization (PPO) is a policy gradient method widely used in high-dimensional, complex control tasks [1]. PPO learns the policy network $\pi(a \mid s;\theta)$ and outputs the probability of selecting each action in a given state. Its core idea is to use probability ratios to measure the differences between new and old strategies, prevent excessive updates, and introduce a clipping function to ensure that each update is not too aggressive. PPO can handle continuous action spaces and has higher stability and convergence speed.

3. Automated driving target detection based on deep reinforcement learning

In autonomous driving systems, object detection serves as the core task of the perception module, and its accuracy directly impacts the reliability of subsequent path planning and decision-making processes. Historically, researchers have primarily relied on non-reinforcement learning algorithms to build object detection models, including traditional image processing techniques, machine

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learning-based classifier models, and the widely adopted deep convolutional neural networks (CNNs) in recent years. These methods typically follow a supervised learning paradigm, training models using large amounts of labeled data to achieve recognition and localization of objects such as vehicles and pedestrians. With the development of sensor technology, multi-modal fusion methods such as the integration of cameras and lidar have also become important means to enhance detection robustness. Although the aforementioned methods have made significant progress in terms of accuracy and efficiency, they largely rely on static data-driven modeling and struggle to fully adapt to the highly dynamic and decision-interactive demands of autonomous driving scenarios [3].

In recent years, deep learning models have been widely used in object detection, significantly improving the performance of autonomous driving perception systems. Among them, anchor-based methods such as Faster R-CNN and the YOLO series achieve a good balance between detection accuracy and speed; anchor-free methods such as FCOS and YOLOv8 further simplify the structure and significantly improve training stability; end-to-end methods such as DETR with a Transformer structure have driven a revolution in detection paradigms. In addition, semantic segmentation networks such as SegFormer and PSPNet can assist in vehicle contour detection and scene analysis tasks, while also helping to improve the overall system's understanding capabilities [3].

Chen et al. (2024) proposed an improved YOLOv8s model to address the problem of detecting small targets in autonomous driving. This model adds 160×160 feature maps, an adaptive feature fusion module, and an improved attention mechanism, significantly enhancing the model's perception capabilities for multi-scale targets. Experiments show that even with the introduction of GSConv, the model still achieves 53.7% and 53.5% mAP on the SODA10M and BDD100K datasets, respectively, with a significant increase in frames per second. The model's potential for application in complex traffic scenarios has been verified [4].

Moussaoui et al. (2024) propose an improved license plate detection and recognition system to enhance the accuracy of license plate recognition in complex environments. The modified model integrates YOLOv8 with OCR, using an anchor-free architecture for license plate localization. It combines image preprocessing techniques such as K-means clustering, binarization, and morphological operations to improve character clarity, and uses EasyOCR to perform character recognition. Through comparative experiments with various existing models such as Mask R-CNN and hierarchical CNN, this method demonstrated superior performance in terms of detection accuracy (99%) and recognition accuracy (99.95%), and exhibited strong robustness under diverse image conditions. This study provides an efficient solution for license plate recognition tasks in autonomous driving scenarios [5].

4. Automated driving path planning based on deep reinforcement learning

In autonomous driving systems, path planning is a key module that connects system perception and system control. Its goal is to generate a safe and efficient driving route for autonomous vehicles. In previous conventional studies, researchers mainly used other non-reinforcement learning methods to plan paths, including heuristic search algorithms such as A* and Dijkstra; optimization algorithms such as dynamic programming and genetic algorithms; and sample-based random trees such as RRT and PRM. These methods have a clearer structure and more stable calculations, but they are often based on the assumption of a static environment, making it difficult to adapt to the dynamic changes in real-world traffic. This limits their performance in high-dimensional continuous action spaces [6].

In recent years, the continuous development of DRL has brought new solutions to path planning tasks in dynamic traffic environments. Unlike traditional methods that rely on rules or prior knowledge to construct strategies, the DRL method can autonomously learn complex environmental

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parameters and derive optimal path planning solutions. This gives it significant advantages in dynamic obstacle avoidance, real-time decision-making, and continuous control [6].

Xu et al. (2024) proposed using the deep deterministic policy gradient (DDPG) algorithm to achieve autonomous navigation and obstacle avoidance path planning for autonomous vehicles, addressing the poor generalization ability of traditional path planning methods in high-dimensional continuous action spaces. This method builds a vehicle motion system based on the Ackermann steering model and optimizes continuous control behavior through the Actor-Critic architecture. Through the comparative tests with DQN and DDQN in the Gazebo simulation environment, DDPG demonstrated higher navigation success rates (97%), shorter path times (45.3s), and faster convergence speeds. This indicates that the application of DDPG can significantly improve the navigation performance of systems in complex dynamic environments [7].

Hao (2025) et al. systematically studied the performance of various reinforcement learning algorithms in different path planning scenarios to improve the path planning capabilities of autonomous driving in complex dynamic environments. They analyzed the strategy modeling capabilities of algorithms such as DQN, A3C, PPO, and MADDPG. Through experiments, they pointed out that these reinforcement learning methods have higher obstacle avoidance success rates, path efficiency, and adaptability compared to traditional methods. In particular, the multi-agent algorithm MADDPG achieved shorter paths, lower collision rates, and higher success rates in experiments, showcasing its potential for application in multi-vehicle cooperative path planning. Among them, the multi-agent algorithm MADDPG demonstrated shorter paths, lower collision rates, and higher success rates in experiments; the PPO algorithm adopted a pruning strategy, achieving higher training stability and convergence speed, and also outperformed traditional methods DDPG and SAC in terms of path length and energy consumption control [8].

Yang and Liu (2024) proposed an improved deep reinforcement learning path planning algorithm, DRL-PP, to address issues such as training instability and slow convergence in traditional DQN path planning. This method uses a three-layer multi-layer perceptron (MLP) to construct a decision network, while combining a dual network structure with a dynamic ε-greedy strategy to optimize the training process and design a more guiding cubic penalty reward function to improve path optimality and convergence speed. In their simulation experiments, compared with traditional DQN and Actor-Critic methods, DRL-PP demonstrated superior performance in terms of training stability, path optimality, and convergence speed, exhibiting greater robustness and higher computational efficiency [9].

Chen et al. proposed a hierarchical path planning and control framework. This method combines a double deep Q-network (DDQN) with a high-order control Lyapunov function (HOCLF)–high-order control barrier function (HOCBF)–quadratic programming (QP) controller. It uses the upper-level DDQN module for decision-making, outputting discrete lane-changing actions such as maintaining the lane, turning left, or turning right, and then passes these to the lower-level HOCLF-HOCBF-QP controller, enabling precise trajectory tracking and collision avoidance under dynamic constraints. In subsequent simulation experiments, the system performed well in complex multi-lane traffic scenarios, achieving efficient and accurate obstacle avoidance, and demonstrating excellent online computing performance [10].

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5. Limitations and future prospects

5.1. The gap between virtual and real environments

When training autonomous driving algorithms, researchers typically use simulated environments such as HighwayEnv [1] to create virtual simulations of real-world traffic conditions. However, the data in these environments is difficult to perfectly match real-world scenarios, as it is often relatively idealized and lacks the noise and outliers found in the real world. This can lead to overfitting in the trained models, preventing them from achieving the desired results in practical applications.

To address this issue, researchers have developed methods such as Sim2Real technology, digital twins, and transfer learning to make the simulated environment more similar to the real environment. In addition, parallel intelligence technology combines virtual and real environments to provide real-time feedback on learning results, further improving the adaptability of the model [11]. However, simulated environments still cannot fully replicate the complexity of the real world, especially the effects of complex natural factors such as weather and lighting. With the continuous advancement of technology, these issues are gradually being resolved, but it is still difficult to completely eliminate the gap between simulation and reality.

5.2. The “black box” problem of DRL algorithms

The high complexity of DRL models means that their decision-making processes are often seen as a “black box,” making it hard to understand the specific reasons behind their decisions. This lack of explainability increases the risk of using them in real-world applications like autonomous driving.

Currently, a common solution is explainable artificial intelligence (XAI) technology, especially Shapley Additive Explanations (SHAP) values, which enhance the transparency and credibility of the decision-making process by quantifying the contribution of each input feature to the model's decision [12]. However, although these methods can effectively improve interpretability, they still have the problem of high computational overhead and are still difficult to completely solve the “black box” problem in complex feature spaces. With the improvement of computing power and the continuous optimization of algorithms, it is expected that this problem will be further improved in the future.

Although deep reinforcement learning currently has certain limitations in its application to autonomous driving, with continuous technological advances, particularly in the areas of simulation-to-reality conversion and model interpretability, these issues will be gradually resolved in the future. Autonomous driving technology will then find wider application, fundamentally transforming people's lives.

6. Conclusion

This paper reviews autonomous driving target detection and path planning technologies based on DRL. With the development of intelligent connected vehicle technology, autonomous driving has become an important research direction for future transportation. Autonomous driving systems rely on precise target detection and efficient path planning to achieve autonomous driving in complex and dynamic traffic environments. Deep reinforcement learning, as a learning-based decision-making method, can continuously optimize decision-making strategies through repeated training in simulated environments, overcoming the limitations of traditional rule-based systems and providing greater adaptability and flexibility.

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This paper explores the application of deep reinforcement learning in two key areas: autonomous driving target detection and path planning, and analyze target detection technology based on DRL, particularly its performance in improving detection accuracy and handling complex traffic environments. At the same time, the advantages of deep reinforcement learning in path planning, such as dynamic obstacle avoidance and real-time decision-making, are also discussed in detail. Compared with traditional methods, DRL demonstrates outstanding performance and optimization capabilities in high-dimensional continuous action spaces.

However, despite the enormous potential of deep reinforcement learning in autonomous driving, it still faces some challenges, such as the gap between simulation and real-world environments and the "black box" problem of models. With technological advancements, particularly in the areas of simulation-to-reality conversion and improvements in explainability techniques, these issues are expected to be resolved. This paper provides theoretical support and technical references for future autonomous driving research, thereby driving the development of this field.

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