Artificial Intelligence Gamers Based on Deep Reinforcement Learning

Haolin Wang

Chongqing DEPU Foreign Language School, Chongqing, China

whlcvbn3456@gmail.com

Abstract. This study investigates the design and implementation of Artificial Intelligence (AI) game players based on deep reinforcement learning, offering a novel approach to autonomous decision-making and strategy acquisition in intelligent games. Initially, the fundamental principles and algorithms of deep reinforcement learning are introduced, along with the fusion of deep learning and reinforcement learning. Subsequently, existing research is reviewed, and the pros and cons of current methodologies are examined, highlighting the underlying issues and challenges. The utilization of AI players in mainstream games is then introduced, and the influence of AI players on contemporary games is analyzed. Through this analysis of AI players in mainstream games, the strengths and weaknesses of current AI players are identified, and recommendations for optimizing them are provided. This study holds significant implications for guiding the design and development of intelligent game players, while also enriching the application of deep reinforcement learning within the gaming domain.

Keywords: Deep Leaning, AI Gamers, Machine learning.

1. Introduction

With the continuous development of intelligent technology, deep reinforcement learning, as an important algorithm model, has been widely used in various fields [1-5]. As an environment full of challenges and changes, intelligent games provide an ideal application scenario for deep reinforcement learning. This study aims to explore and design AI players based on deep reinforcement learning to improve the autonomous decision-making and strategy learning ability of game players.

The design of intelligent game players is of great significance to game development and artificial intelligence research. Through the application of deep reinforcement learning algorithm, the game experience of game players can be improved, and the playability and fun of games can be improved. At the same time, studying intelligent gamers can also promote the application of deep reinforcement learning in other fields, such as autonomous robots and intelligent decision systems. Some specific challenges encompass: determining the definition of the gaming environment and the action space, selecting an appropriate state representation and observation method, devising effective deep neural network architectures, and formulating training algorithms and strategy update procedures.

This paper is divided into five parts. The introduction introduces the background, significance and purpose of the research, and summarizes the structure of the paper. The second part gives a brief introduction to deep reinforcement learning, including its basic concepts and algorithms, and explores its integration with intelligent games. The third part analyzes the existing methods and the problems to be solved in the field of intelligent game player design by summarizing the existing research. The fourth part elaborates the research methods and model design, including game environment definition, state representation selection and deep neural network structure design. The last part is for discussion and future work, summarizes the important results and innovations of the research, and discusses the future improvement and application direction.

2. Introduction to Deep Reinforcement Learning

2.1. Basic Concepts and Algorithms of Reinforcement Learning

Reinforcement learning shown in Figure 1 is a learning method that maximizes cumulative rewards through trial and error learning. It describes the problem based on a Markov Decision Process (MDP) model consisting of states, actions, rewards and strategies. Common reinforcement learning algorithms include Q-learning, SARSA and Deep Q network (DQN). These algorithms perform action selection and strategy optimization by using value functions or strategy functions.

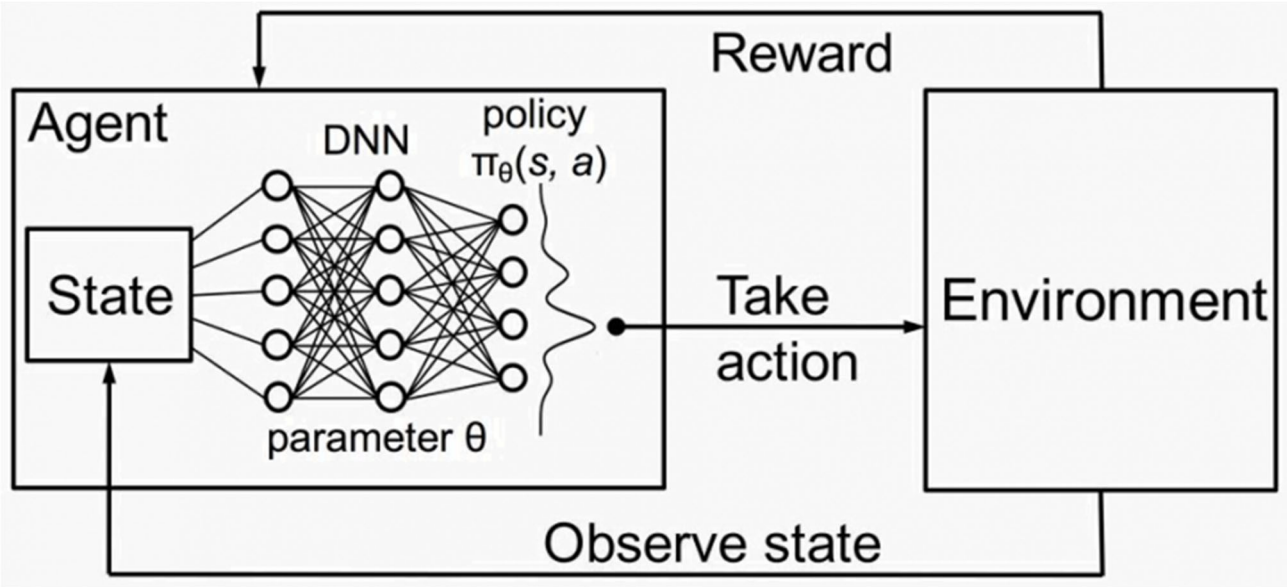

Figure 1. The illusration of the deep reinforcement learning [6].

2.2. Combination of Deep Learning and Reinforcement Learning

Deep learning is an approach that efficiently learns feature representations and recognizes patterns through the construction and training of multi-layer neural networks [7-10]. In the context of reinforcement learning, deep reinforcement learning leverages deep neural networks as tools for approximating value functions or policy functions, integrating them with traditional techniques. This combination can improve the efficiency and performance of learning, and show the adaptability to complex environment and high dimensional state space.

2.3. The Application Prospect of Deep Reinforcement Learning in Intelligent Games

In intelligent games, the application of deep reinforcement learning has broad prospects. By applying deep reinforcement learning to the design of intelligent game players, they can be equipped with stronger decision-making ability and autonomous learning ability. Intelligent gamers can continuously learn and optimize strategies by interacting with the game environment, resulting in higher game completion and player satisfaction. At the same time, the design of intelligent game players can also promote the promotion and application of deep reinforcement learning in other fields.

3. Products Currently Used by AI Players and Their Role

There are a lot of games that are using AI players to make the game more challenging or provide a better gaming experience. Here are some well-known games that use AI players, with a brief overview of what it does:

1. League of Legends: AI players take on the role of opposing teams in this game, giving them the opportunity to play against real players. AI players can simulate different levels of skills and strategies

according to different difficulty levels, providing practice opportunities for novice players, but also providing more difficult challenges for experienced players.

2. PlayerUnknown's Battlegrounds: In the game, AI players are used to make up for a shortage of players. They act as virtual characters in the game, simulating the behavior of real players in order to increase the tension and competition of the game.

3. FIFA series: AI players play the role of uncontrolled players in football games. They make their own decisions based on the situation and strategy of the game and collaborate with players controlled by the player to enhance the game's intensity and challenge.

4. Call of Duty series: AI players take on the role of enemy or teammate in the game's single player mode, fighting or cooperating with the player on missions. Their purpose is to increase the game's enemy forces or provide support to enhance the game's combat experience.

The AI players in these games show varying degrees of intelligence in simulating the behavior and decisions of human players, making the games more challenging, entertaining, and realistic. At the same time, the presence of AI players can also fill the scene where the number of players is insufficient and ensure the smooth progress of the game.

The combination of reinforcement learning with AI players is a common method used to train AI agents to learn and improve their decision-making abilities in games. Here are the general steps for combining reinforcement learning with AI players:

1. Environment modeling: Abstracting the game environment into a state-action space. States contain all kinds of information in the game, and actions are actions or decisions that the AI player can take.

2. Strategy definition: Define the AI player's strategy, that is, the way to choose an action in a given state. Common strategies include stochastic strategies and deterministic strategies.

3. Reward design: Design reward functions to evaluate the behavior of AI players. The reward function evaluates the player's actions based on the game's goals and rules. Rewards encourage the AI player to take good actions, while punishments punish bad behavior.

4. Reinforcement learning training: The use of reinforcement learning algorithms, such as Q-Learning or Deep Q-Network (DQN), through interaction with the environment, let AI players make action choices according to the current strategy, and update the strategy to maximize cumulative rewards. During the training process, AI players learn optimization strategies through trial and exploration, and gradually improve their decision-making ability.

5. Model evaluation and iteration: During the training process, the performance of AI players can be evaluated, and their performance can be viewed by playing against other AI players or real players. Based on the evaluation results, the model can be adjusted, parameters optimized, or training strategies changed to further improve the performance of AI players.

The fusion of reinforcement learning with AI players allows AI agents to autonomously acquire strategies and enhance decision-making skills by interacting with their environment. Through this iterative process, they gradually adapt and elevate their performance in the game, ultimately exhibiting intelligent gameplay behaviors. This integration is extensively employed within the realm of gaming, significantly enhancing the overall AI gaming experience.

4. Discussion

This paper discusses a new experimental improvement idea that can be considered in future work at present. The game intelligent player method based on deep reinforcement learning mainly includes four aspects: image processing, strategy network, value network and objective function.

First, image processing is the conversion of game images into numerical features that can be used by neural network models. Convolutional Neural Network (CNN) [11, 12] is used to process the game images, and the feature information in the images is gradually extracted through the convolutional layer and the pooling layer. Secondly, a strategy network is a network model for predicting and making decisions on feasible actions in the game. Its input is the feature vector of the game state, and

its output is the probability distribution of each action. In order to explore the variety of strategies in the game, the strategy network uses random processes to sample to produce different decisions.

Third, value network is a network model that evaluates the value of game state and action. Its input is the feature vector of game state, and its output is the value estimate of the state, or the return prediction after performing an action. Value networks can help policy networks converge more quickly to optimal decisions.

Finally, the objective function is the loss function used to adjust the parameters of the neural network model, and it is also the most core part of deep reinforcement learning. Common objective functions include PolicyGradient, Value Function and Actor-Critic.

5. Conclusion

This paper presents an examination of the application of deep reinforcement learning within the realm of gaming. Currently, reinforcement learning technology is predominantly employed for AI players in games, notably in titles such as Final Fantasy 14 and League of Legends. Acknowledging the current limitations of this approach, the paper also explores a fresh experimental concept. Frequently, players express dissatisfaction with the simplicity of battling AI opponents in games. To address this issue, a potential solution involves integrating deep learning with adversarial training, continually refining AI player strategies through interaction with the gaming environment and challenging them to adapt by competing against real players.

However, there are still shortcomings in this paper. For instance, the proposed idea has not yet been realized. In the future, further research will aim to implement and validate this concept through practical experimentation.

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