Exploration and Analysis of Game Algorithms in Desktop Games

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Abstract. Playing chess and cards is a popular leisure and entertainment desktop game in the international community. Chess competitions also play a decisive role in the world. From 1956 to now, the man-machine confrontation in chess competitions has attracted much attention. According to the existing research, this paper analyzes the application of game algorithm in desktop games, and makes a deeper analysis of game algorithm. In the research process, we mainly use literature research method and comparative analysis method to analyze the game algorithm. Of course, explore the bold conjecture of the innovative algorithm, compare the advantages and disadvantages of different algorithms, make up for each other in the simulation quality, the ability to deal with incomplete information and the ability to adapt to the environment, design the flow chart and analyze the feasibility and possibility of the innovative algorithm, and strive to solve the problem of decision-making efficiency, search efficiency, and then the confrontation mechanism will also be greatly improved.

Keywords: Game Algorithm; Tabletop Game; Monte Carlo Algorithm.

1. Introduction

The real beginning of the game algorithm is the minimax search algorithm first discovered and proposed by von Neumann in 1928. This discovery also provides a great contribution to the subsequent research on solving chess, so it opens the prelude to the application of the game algorithm in desktop games. Further developed to 1997, a world-renowned news report was made public -- the dark blue computer algorithm program defeated the world champion Garry Kasparov in the international chess tournament [1]. This news caused a sensation all over the world, and also caused a real upsurge of research on the game algorithm in desktop games. Then, many types of game algorithms were born, especially the application of Monte Carlo algorithm to beat the professional go players in the go competition, which further proved the efficiency advantage of Monte Carlo algorithm. Similarly, the human brain innervates the mental computing power of human beings. Researchers have developed neural networks by analogy with human brain nerves. In the algorithm, some scene evaluation models combined with the divine network are extracted through the reasoning of some incomplete chess models, and some game trees are searched and trained [2]. Based on the development of neural network, the feasibility of deep learning and reinforcement learning algorithm is also proposed, so the innovative algorithm of multivariate combination has become a hot research topic. In some desktop games, researchers have found that different playing methods in the game will also lead to different research results in the application of the same algorithm. Especially in card games, unlike chess games, it has very clear selection conditions for both sides of the game. However, card games have different numbers of cards, different decision-making effects, and various selection conditions. Based on this question, researchers divide them into complete information game and incomplete information game. In the research of complete information game, algorithms such as Monte Carlo algorithm, alpha beta pruning algorithm and reinforcement learning algorithm have become good choices in research. This paper mainly makes a large number of comparative exploration and analysis of different game algorithms used in different literatures at home and abroad, including the analysis of different research status at home and abroad, as well as the types of algorithms, innovative algorithms in recent years, For example, the Monte Carlo tree search algorithm combined with convolutional neural network, as well as the algorithm method and process, and the advantages and disadvantages of some functions of the algorithm, have caused some new ideas and ideas [3]. For this new idea, carry out comparative exploration and process ideas, and design a flow chart that conforms to logical thinking. Including considering the practicability of this new game algorithm in the future, the advantages of high search efficiency and high decision efficiency in the battle mode of desktop games are migrated to the games with high dimension and high complexity in the dynamic space environment, so as to solve the problem of decision-making in such games. However, there are still some unsolved problems in incomplete information game. This new algorithm can also make up for the problem that alpha beta pruning algorithm can not deal with incomplete information game. Including in the aspect of AI, AI agents are used to continuously design and iterate to simulate board games, and the degree of "humanization" of AI test results, In addition to the inspiration of AI test, a large part of it is based on the effectiveness and decision-making ability of algorithm decision-making [4]. Whether its decision-making thinking can reach the "human" level is also a problem studied by many researchers at present.

2. Comparative Analysis of The Current Situation at Home and Abroad

For the research of game algorithm in desktop games, the domestic research actually focuses more on the traditional game tree algorithm, but because the traditional Monte Carlo tree search algorithm is difficult to solve the balance between exploration and utilization, it gradually studies and analyzes the more new Monte Carlo tree search algorithm combined with convolutional neural network [5]. In the research process, China attaches great importance to the optimization of rule decision-making. Through the performance comparison of various algorithms, the efficiency of game rule decision-making has been greatly improved. At home, Chinese culture is broad and profound, which is contained in a variety of chess and card games. Similar to the Chinese card game "Three Kingdoms kill", there are many cultural outputs, such as the setting of roles, the restraint relationship between role cards, and the arrangement of rules and reward systems, which are closely related to culture. Foreign research will have certain cultural restrictions. In the process, it will be hindered by some areas of cultural knowledge, resulting in the lack of thorough research. Therefore, the direction of foreign research tends to be mass desktop games, and foreign algorithm research focuses on modern and innovative game algorithms, especially reinforcement learning algorithm, which is hot in the application of desktop game algorithms. In the research process, foreign algorithms put more emphasis on the framework and ideas of implementing the algorithm, and can provide AI with more powerful game decision-making training in terms of computing power. Not only that, it is also cutting-edge for foreign countries to master the data and computing power of desktop games, and the scale of the database also makes computing power more accurate.

Monte Carlo tree search has become the most frequently used algorithm at home and abroad, and it has also made a qualitative leap in dealing with some incomplete information in desktop games. At present, The Monte Carlo tree search algorithm combined with deep neural network is the research direction of most researchers at home and abroad [6]. The deep neural network architecture has an input layer, including six neurons. In the process of the game between the two opponents, it represents the health, endurance, direction and the distance between the opponent and the agent. The behavior tree architecture is the most important way to study and understand algorithms at home and abroad. the behavior tree is a tree structure, similar to a tree with branches, each branch has multiple nodes, which will change through changes to different environments and actions, just like every situation in the game [7]. The behavior tree is mainly used to traverse the behavior information in each situation, so as to find the optimal action decision, and thus participate in the whole game world.

3. Overview a Mainstream Technology

3.1. Alpha-Beta Pruning Algorithm

Alpha beta pruning algorithm is composed of three core principles, game tree model, minimax search and pruning logic. According to its tree structure analysis: suppose a max value point a is the lower limit of the optimal score of the desktop game player, and a min value point B is the upper limit of the optimal score of the desktop game player. If the score of the player at point a is higher than that of the player at point B, then search down from the root node a to point B, and find that the value of point B cannot exceed the max value, and then prune all child nodes including the node at point B. Such a search method does not need to search any node (situation) one by one, which greatly improves the search efficiency and decision-making efficiency.

In the zero sum game algorithm, it is usually accompanied by the minimax algorithm of alpha beta pruning algorithm [8]. Especially when there is a conflict of interest between different players in the process of the game, both sides need to win or lose. If the value of Party A is large, and the best strategy is to take the maximum and minimum profit, then Party B should strive to reduce its losses and maximize its interests.

3.2. DDPG Algorithm

Markov process algorithm and DDPG algorithm are two prominent algorithms in the value strategy of reinforcement learning algorithm. In fact, in practical application, the decision-making process of DDPG algorithm (the cycle process between agents and the environment) is optimized under the framework of Markov process algorithm. After research and analysis: there will be an environment in the game. According to this environment, there will be a game state s. According to this state, an action act will be made. According to this action, a new environment will be generated. This new environment will generate a new game state s1 and the expected reward. This new state will continue in the new environment, thus forming a cycle. The optimization of strategy value process makes the algorithm more convenient when dealing with incomplete information desktop games.

So, exploring how agents can make action decisions based on the environment. What the agent needs most is to be able to sense the surrounding environment and give a response according to the surrounding situation, then this response is an action. What is needed for exploring this action is a sensing light [9]. Through this sensing light, the agent can judge whether the object or obstacle sensed by exploration is hit, and then get the return value.

3.3. Monte Carlo Tree Search Algorithm

Monte Carlo tree search algorithm is the most widely used algorithm in the research of desktop game algorithm. It is mainly a tree structure, and each node is equivalent to a situation. MCTS mainly goes through four processes: selection, expansion, simulation and backpropagation [10]. Select a suitable situation from the root node (initial situation) in turn, expand an optimal action according to this situation, generate a series of strategies for this action, and combine this strategy to produce a result in the situation, which will be backpropagated to the final expected reward value, and the game ends. Then the next sentence will continue to make the next round of selection. The Monte Carlo tree search algorithm can adapt to different static and dynamic environments for this tree search method, and has strong environmental adaptability.

James Goodman et al proposed a conversion function T (s, a). s. A represents the player's game state in a game environment and the decision actions made by the player in this state and environment [11]. The last step of MCTS returns, namely the player function P (s), which returns the expected value of the final reward value to the player's states. In the selection and expansion stages, some decision strategies, such as rou (s), rexp (n), tree (n), can be used in the process of searching for nodes in the tree. The data of each node can be saved.

4. Comparison of Typical Algorithms

According to the three types of algorithms analyzed and summarized above, in terms of simulation quality, Alpha Beta pruning algorithm can achieve higher simulation quality with fewer training times, which indicates that its search efficiency is very high. Compared with the Alpha Beta pruning algorithm, the search efficiency of the Monte Carlo tree search algorithm is inferior, because it requires each node to search, which will greatly consume the search time and reduce the search efficiency. What is needed in dealing with complex games such as incomplete information is the decision-making ability of the game algorithm. Alpha Beta pruning algorithm is weak, and the Monte Carlo tree search algorithm and DDPG algorithm have fast and accurate decision-making ability. However, the two are different in spatial environment. For example, MCTS can show its fast characteristics in the decision-making process in the high-dimensional spatial environment, and the DDPG algorithm performs accurate calculation in the controllable environment to achieve the optimal decision-making effect.

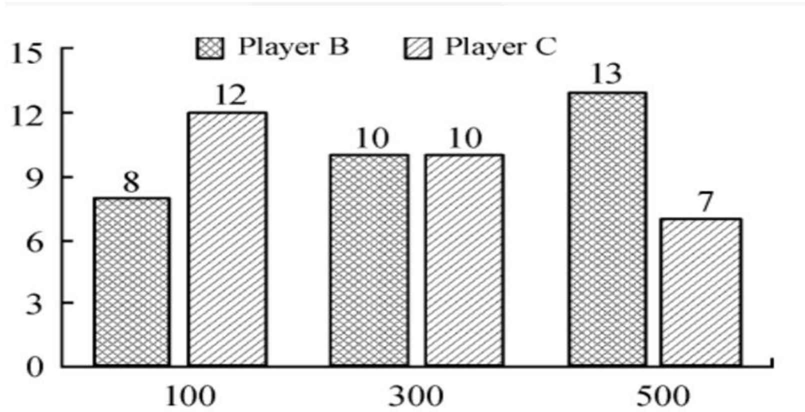

Fig 1. Comparison between Segmented Algorithm and Global Alpha Beta Pruning Algorithm [10]

As shown in figure 1, this is a comparison of the winning situations of two different game programs, Prayer B and Player C, in the training characters. The vertical axis represents the number of victories, and the horizontal axis represents the number of training sessions [10].

It can be seen from the figure 1 that the two are compared: Firstly, when the training times reach 100, playerC has greater advantages over playerB, at this time, playerB obviously sees that the training times are insufficient, and the computing power cannot reach the expected results. Secondly, when the number of trainings reaches 300, playerC is equal to playerB at this time, which indicates that playerB has mastered some methods to gradually surpass playerC, and its computing power is gradually improving. Thirdly, when the number of trainings reaches 500, Player B gains greater advantages in playing with Player C. At this time, playerB can predict the decision-making actions of player C and take defensive measures. The game program of Alpha Beta pruning algorithm can achieve significant advantages in fewer training iterations, demonstrating its efficient search efficiency.

5. Innovative Algorithm

Based on the comparison among the three different types of algorithms analyzed above, a bold guess is proposed whether these three different algorithms can be combined to solve more complex desktop game problems. First, explore the possibility. The combination of Alpha Beta pruning algorithm and Monte Carlo tree search algorithm has been studied and verified by researchers. The combination of the two algorithms greatly makes up for the low search efficiency of Monte Carlo tree search algorithm. In the selection process of Monte Carlo tree search algorithm, the minimax search method of Alpha Beta pruning algorithm is used, instead of searching the nodes of MCTS one by one, which greatly saves the search time and greatly improves the search efficiency. Although the combination of the two makes up for the shortcomings of search efficiency, the Monte Carlo tree search algorithm and Alpha Beta pruning algorithm still have shortcomings in environmental adaptation. One is that the calculation accuracy is not high in dynamic environments, and the other is that the adaptability to dynamic environments is relatively weak. After exploration, it is found that the DDPG algorithm can accurately calculate in its controllable environment, so the combination of these three algorithms can make up for their respective shortcomings relatively perfectly. Moreover, after more in-depth exploration, MCTS and DDPG algorithms can optimize the decision of α - β pruning algorithm, so that the combination of the three algorithms can have the ability to solve incomplete information desktop games.

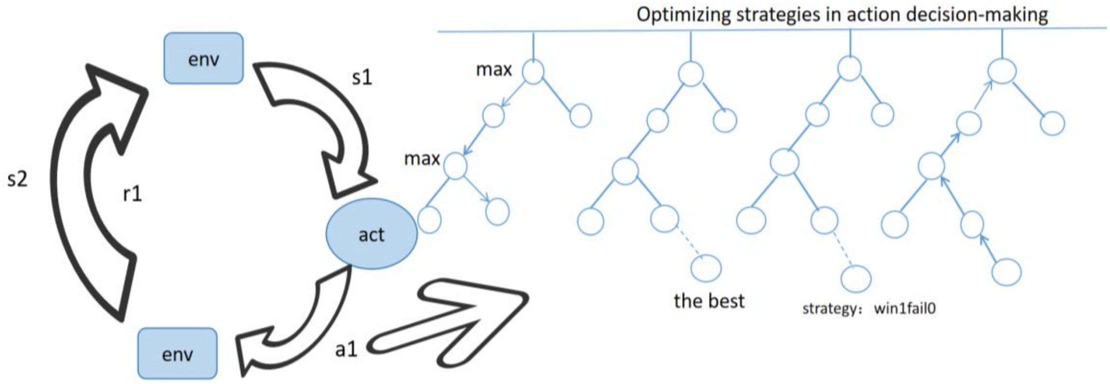

Fig 2. Flowchart of Innovative Algorithm

According to the analysis of the Fig. 2, the interaction cycle between the environment and the agent is still carried out according to the process of the DDPG algorithm. The state S of the agent is generated in a game environment, action decisions are made, and a new state is generated in the generated new environment. Then the reward expectation value corresponding to the game is given, and the cycle continues. The Alpha Beta pruning algorithm is combined with the Monte Carlo tree search algorithm when making the best action decision, especially in the selection step, the Alpha Beta pruning algorithm minimax search is used to find the best action and make the decision. The decision results follow the process of the Monte Carlo tree search algorithm, go back to the step, and then continue to transmit to the agent and the environment to get the reward value.

6. Conclusion

If Game Algorithms are widely used in desktop games, but they still need to be more refined. Each algorithm has different characteristics and advantages of each algorithm. Give full play to the maximum advantages of each algorithm to achieve an ideal effect. The machine AI decision computing power of game algorithm between battle modes in desktop games can be transferred and applied to more fields to further realize cross field development. Similarly, the innovative algorithm mentioned above can also develop its advantages. The improvement of the three algorithms, especially their adaptability in the environment, will migrate the decision algorithm in their desktop games to a higher dimension model game to solve more complex game rules and strategy algorithms like Turret 2. Nowadays, reinforcement learning algorithms and large model driven algorithms are gradually thriving, especially the application of reinforcement learning in desktop game algorithms is gradually developing, which is committed to solving more complex chess and card games with incomplete information. Therefore, incomplete information game algorithms can also get many breakthrough results. So, has the innovative algorithm been verified in actual combat? Or is there a better combination of algorithms to solve complex problems? The exploration of game algorithms for desktop games continues.

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