The Application of Artificial Intelligence in Chess Game

Chenyu Zhuang[a]
International Digital Economy College, Minjiang University, Fuzhou, Fujian, China

Keywords: Artificial Intelligence, Chess Game, Search Algorithms.

Abstract: Because of its extremely high complexity, the chess game has long been a key field in the development of artificial intelligence. With the continuous progress of science and technology, computing power is increasing day by day, and more complex search algorithms and evaluation functions are widely used, which promotes the continuous improvement of artificial intelligence chess power. There are many kinds of chess games, and artificial intelligence has shown great strength in many complex chess projects, even surpassing the top human chess players. This paper focuses on the four kinds of chess, Chinese chess, Black and White chess, Gobang and Go to carry out in-depth discussion, systematically analyze the application of artificial intelligence in board games, and discuss the limitations of existing artificial intelligence board games, and then forecast the development trend of future board games. This paper aims to summarize the current scientific and technological level of artificial intelligence games and put forward suggestions for the next development.

1 INTRODUCTION

In the course of the development of artificial intelligence board games, in 1928, the two-person zero-sum minimax theorem proposed by v. Neumann, the father of computers, laid the theoretical cornerstone of board games. In 1950, Claude Ellwood Shannon proposed a computer scheme for chess(v. Neumann, 1928; Li & Wu, 1995; Shannon, 1950). The "Mac Hack VI" chess program, which appeared in 1967, could beat chess beginners, and by the 1990s IBM's Deep Blue computer had successfully defeated world chess champion Garry Kasparov. In 2016, Google's AlphaGo successfully defeated Go world champion Lee Sedol, allowing the world to see the strength of artificial intelligence board games. In 2017, the AlphaGO team launched AlphaGO Zero without human training, relying only on self-reinforcement learning, surpassing all previous versions and pushing the artificial intelligence game to a new height.

In the field of artificial intelligence board games, board game provides a valuable experimental scene for the development of artificial intelligence, constantly promote the development of artificial intelligence technology, but also promote the development of chess sports, provide people with better chess ideas, provide a variety of training tools, and makes an important contribution to improving the competitive level of chess players. In artificial intelligence board games, search algorithms are used to select strategies, such as depth-first, breadth-first, iterative deepening search, Monte Carlo tree search, alpha-beta pruning search, heuristic search, etc. In terms of evaluation function, the advantages and disadvantages of chess can be evaluated according to different rules and characteristics of chess games. It can also be learned through supervised learning and using a large number of human chess pieces, or through reinforcement learning, artificial intelligence can play chess by itself to continuously improve its chess ability. Focusing on the above search algorithms and evaluation functions.

This paper gives a detailed introduction to the four kinds of chess, Chinese chess, black and white chess, Gobang and Go, and artificial intelligence game methods, as well as the future development of artificial intelligence games, integrate more artificial intelligence technology, and look forward to a wider range of applications, hoping to provide greater value to the field of artificial intelligence.

[a] https://orcid.org/0009-0006-0094-2884

Zhuang, C.
The Application of Artificial Intelligence in Chess Game.
DOI: 10.5220/0013702400004670

In *Proceedings of the 2nd International Conference on Data Science and Engineering (ICDSE 2025)*, pages 586-590
ISBN: 978-989-758-765-8

2 METHOD

2.1 The Application of Artificial Intelligence in the Field of Chinese Chess

In the field of Chinese chess games, artificial intelligence has transformed the landscape of this board game. The chessboard is 9×10 in size, and the moves are relatively fixed. Its complexity is lower than that of Go. Traditional search algorithms, heuristic search algorithms, and evaluation functions can be utilized to find better solutions. However, compared to Go, it has a relatively lower dependence on deep learning. The rules of chess are relatively clear, and it has more quantifiable evaluation indicators. For example, different pieces such as the chariot, the horse, the cannon, and the soldier have different values, and these values can provide references for situation assessment. Therefore, the situation score can be calculated through relatively clear evaluation functions, which makes the calculation of chess based on traditional rules easier to understand and operate.

Based on the analysis of the shortcomings of a single permutation table, the higher-ups proposed a permutation table algorithm based on hash technology. In this algorithm, the first permutation table adopts a depth-first strategy, while the second one employs the always-overwriting strategy. Through this approach, the double permutation table can effectively improve the hit rate of the system, avoid the problem that shallow records in the depth-first table cannot be stored, and solve the defect of the always-replacing table that ignores the search depth. Experimental results show that the double permutation table has obvious advantages in improving the search efficiency of the Chinese chess human-machine game system (Gao & Guo, 2008).

Yue et al. conducted research on improving the efficiency of the α - β pruning algorithm. By referring to the existing heuristic methods in chess, they proposed to utilize permutation table heuristics, static evaluation heuristics, dynamic heuristics (killer heuristics and historical heuristics), and expand the window for internal iterations to deepen the generation of better move arrangement schemes. This scheme has strong heuristic capabilities. The experimental results show that it can significantly improve the efficiency of the α - β pruning algorithm (Yue & Feng, 2009).

Guo analyzed the roles of the evaluation function and the auxiliary search mechanism in the chess game system, proposed the application of the B* algorithm based on the best-first search strategy, and improved the evaluation function. This method adopts the method of returning correction values, which is fed back from the lower-level nodes to the upper-level nodes, and modifies the optimistic and pessimistic values of the upper-level nodes, so as to continuously shorten the value range and reach the termination condition of the algorithm, making it easier to find the best branch. The experimental results show that the B* algorithm is effective in the chess game and improves the efficiency of search (Guo, 2010).

2.2 The Application of Artificial Intelligence in the Field of Black and White Chess.

In the game of Black and White chess, artificial intelligence provides more powerful learning and training tools, enriching the tactical strategies of black and white chess, and having no small impact on the development of black and white chess. The Black and white chess board is 8×8, a total of 64 grids, and its complexity is far less than Go. When artificial intelligence is looking for the best solution, more search algorithms are used to build game trees for search and evaluation, and less deep learning and reinforcement learning are used. When evaluating the situation, Black and White chess mainly calculates the situation according to the number of pieces, occupying positions and the number of flipped pieces, etc., based on relatively clear rules and through clear evaluation functions.

By combining the estimation process of the generated game tree nodes with the search process of the game tree, Du et al. proposed to use Alpha-Beta pruning and max-min principle methods to search for the best position, optimize the game tree search and valuation function from two aspects and change the search order will improve the efficiency of the pruning algorithm. When the algorithm gives the chosen step, do not stop the search immediately, but search a few steps further on the original estimated possible path, and check again whether there will be accidents, and add auxiliary search methods. The experimental results show the effectiveness of the algorithm, which improves the original algorithm and improves the search speed (Du & Cheng, 2007).

Li studied the game tree search algorithm and proposed a heuristic improvement on the basis of the game tree search algorithm. Heuristic factors include: the double substitution table heuristic, shallow detection heuristic and "killer" heuristic. In node sorting, the method of dynamic selection of node sorting is used, including controlling a certain sort depth, pv node sorting, child node sorting of the "eldest" node and so on. After the above improvement, the experimental results show that the improved heuristic game search is better than the general heuristic search. At the same time, the 0 window heuristic search strategy is used to further improve the search efficiency (Li, 2010).

Peng studied the application of artificial intelligence in Black and white chess, introduced the classic black and white chess algorithm, studied the Monte Carlo tree search algorithm, Q learning algorithm and SARSA algorithm, and applied them in black and white chess. The experiment shows the effectiveness of the Monte Carlo tree search algorithm, Q learning algorithm and SARSA algorithm, which improves the search efficiency (Peng, 2021).

2.3 The Application of Artificial Intelligence in the Field of Gobang

In the field of Gobang (Five-in-a-row) games, artificial intelligence has a significant impact on its development. The Gobang board is typically 15×15 or 19×19, with fewer moves compared to Go and a lower level of complexity. In Gobang games based on artificial intelligence, decisions are often made by directly matching known winnings or draw patterns. For more complex situations, artificial intelligence uses search algorithms to construct game trees for search and evaluation. Gobang relies far less on deep learning and reinforcement learning than Go. The evaluation of Gobang's positions is relatively simple, and the superiority or inferiority of the game can be calculated through quantitative analysis of the board patterns.

Wang conducted in-depth research on the α-β pruning algorithm and proposed an improved game tree search algorithm that combines the five-in-a-row/double-three function, evaluation function, and α-β pruning algorithm. This algorithm first applies the five-in-a-row/double-three function and the evaluation function for judgment. If no suitable chess point is found, it then uses the α-β pruning algorithm for search. The experimental results achieved a human-machine intelligent Go game and verified the effectiveness of the game tree search, improving the algorithm efficiency (Wang, 2011).

Cheng et al. improved the Alpha-Beta search algorithm by studying it and proposed an enhanced version that incorporates local search, static evaluation heuristics, and iterative deepening to boost the efficiency of the Alpha-Beta search algorithm. This experiment tailored the search algorithm to the characteristics of Gobang, achieving the goal of enhancing search efficiency and significantly improving it (Cheng & Lei, 2012).

Shen proposed a Gobang algorithm based on Monte Carlo Tree Search and deep neural networks in response to the study of the branching factors and complexity of Gobang game situations. The algorithm simulates Gobang games using Monte Carlo Tree Search and is fully trained through self-play reinforcement learning. At the same time, a Gobang policy evaluation deep neural network composed of multiple residual blocks is used to evaluate the move positions and sample movements in Gobang games. The residual structure forms cross-layer connections, making the network more stable and easier to train. Using the policy evaluation deep neural network with a residual structure to guide the Monte Carlo Tree Search enhances the intensity of the tree search, resulting in higher quality moves and stronger self-play iterations. Experimental results demonstrated the feasibility of this method and increased the speed of training the Gobang algorithm model agent (Shen, 2021).

2.4 The Application of Artificial Intelligence in the Field of Go.

The introduction of artificial intelligence in the game of Go has completely transformed the development landscape of the world's Go. The AI's Go-playing ability has surpassed that of all Go players around the world, making it the leader in this field. The Go board is 19×19, with 361 intersections. Theoretically, there are 361 possible moves for the first step, and the complexity of the combinations is extremely high, making it one of the most complex board games in the world. Therefore, Go games based on artificial intelligence, rely more on deep learning and reinforcement learning for calculation. The evaluation of the Go board situation is difficult to precisely quantify with simple rules, and the value of the pieces is not fixed. AI uses deep learning models to learn how to evaluate the board situation. This board situation evaluation is based on learning from a vast number of games and feature extraction, rather than using simple rule evaluation and blind calculation.

Through studying the design and implementation of AlphaGo's value neural network, Wang created a Go dataset, reproduced the value neural network model, optimized the algorithm for the network training process, and implemented a 36-layer deep residual value neural network. Finally, he conducted large-scale distributed neural network training and trained a more accurate value neural network. This experiment designed a more precise value neural network that can accurately predict the winning rates of black and white pieces. Compared with AlphaGo's value neural network, improvements were made in dataset creation, network model construction, and large-scale distributed training, enhancing the valuation accuracy (Wang, 2018).

With the aim of reducing reliance on computing power and enhancing algorithm performance, this study focuses on improving the feedback mechanism and neural network of deep reinforcement learning algorithms in computer board game applications. A hybrid deep reinforcement learning model is proposed, featuring a novel neural network structure called the "max-average output layer," which replaces several convolutional layers in the middle of the CNN. This method is based on deep reinforcement learning for board games and employs a Q-value update approach that combines Q-Learning and Sarsa(λ) in the Q-table. Using Microsoft's .Net Framework 4.7.2 and the Microsoft Cognitive Toolkit deep learning library, a Go game-playing program based on deep reinforcement learning was designed and implemented. The performance of the network structure with the "max-average output layer" was verified, and the algorithm performance was improved (Lv, 2020).

The AlphaGo series was trained through human expert supervision learning and self-play reinforcement learning. The AlphaGo team proposed an algorithm based solely on reinforcement learning, without human data guidance, and designed AlphaGo Zero. This version became its own teacher and reduced the utilization of tree search. In this experiment, AlphaGo Zero defeated the previous most powerful AlphaGo version by a large margin. The latter was trained from human data through manual education. However, the former was trained through self-play reinforcement learning, using 40 residual block neural networks for 40 days, achieving better performance (Silver et al., 2017).

3 CURRENT LIMITATIONS AND FUTURE DEVELOPMENT PROSPECTS

The development of artificial intelligence in board games has been rapid. Although AI has defeated top human players in complex games like Go, the progress in some other board games has been relatively slow. Moreover, AI's performance may be affected when facing opponents with different styles and more complex situations. Therefore, the adaptability of AI still needs to be improved. When dealing with complex board game problems, AI requires a large amount of computing resources and time for search and decision-making. Even with some optimization algorithms, it is still difficult to quickly provide the optimal solution within limited computing resources, which restricts its application in scenarios with high real-time requirements. In the long term, enhancing the generalization ability of AI is crucial for its application in board games. AI with strong generalization ability can better adapt to different playing styles and various complex situations, rather than being limited to specific scenarios or patterns. The improvement of the explainability of AI's decision-making process should not be ignored either. Explainability enables humans to understand the decision-making logic of AI more clearly, which is helpful for further optimizing its strategies and enhancing the trust and collaboration between humans and AI in board game interactions. In the future, it is hoped that multiple AI technologies can be integrated to increase computing power, provide the optimal solution more quickly within limited computing resources, adapt to more complex situations, and at the same time, strengthen the generalization ability of AI to handle more complex scenarios and enhance the explainability of its decision-making process, so as to promote greater development and open up broader space for AI in the field of board games.

4 CONCLUSIONS

This article analyzes the artificial intelligence (AI) game-playing methods in four types of board games (Chinese chess, Black and White chess, Gobang, and Go), delving into the application and development of AI in board game competitions. Chinese chess and Gobang to some extent rely on traditional search algorithms and evaluation functions, through which effective situation assessment and decision-making can be achieved. However, due to the highly complex board and vast computational space of Go, it more heavily depends on advanced technologies such as deep learning and reinforcement learning to handle complex game situations. Through detailed analysis of these four types of board games, not only demonstrates how AI has broken through technical bottlenecks and continuously improved the intelligence level of board game competitions but also reveals the different challenges and solutions in the application of AI in different board games. With the continuous integration and development of multiple technologies, AI will also play an increasingly important role in more complex and diverse fields, promoting innovation and development in various industries. The application of AI in board game competitions not only promotes the research of intelligent systems but also provides valuable technical accumulation for exploring complex systems, indicating that AI technology will show a broader and more profound application prospect in the future.

REFERENCES

Cheng, Y., & Lei, X. (2012). Research and improvement of Alpha-Beta search algorithm in Gomoku. Computer Engineering, 38(17), 186-188.

Du, X., & Cheng, J. (2007). The application of game algorithms in the game of Othello. Computer Technology and Development, 17(1), 216-218.

Gao, Q., & Guo, C. (2008). Research on the application of hash technology in Chinese chess computer game systems. Science Technology and Engineering, 8(17), 4869-4872.

Guo, X. (2010). Research and improvement of search algorithms in Chinese chess computer games (Master's thesis, Hebei University).

Li, X. (2010). Design and implementation of an improved game tree for Othello (Master's thesis, South China University of Technology).

Li, X., & Wu, W. (1995). Biographies of world-renowned mathematicians. Science Press.

Lv, Z. (2020). Research on chess game strategies based on deep reinforcement learning (Doctoral dissertation, Central University for Nationalities, Beijing).

Peng, Z. (2021). Application of computer game algorithms in Othello. Modern Information Technology.

Shannon, C. E. (1950). XXII. Programming a computer for playing chess. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, 41(314), 256-275.

Shen, X. (2021). Design and implementation of a Gomoku algorithm based on Monte Carlo Tree and neural networks (Master's thesis, Shenyang University of Chemical Technology).

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., ... & Hassabis, D. (2017). Mastering the game of Go without human knowledge. Nature, 550(7676), 354-359.

v. Neumann, J. (1928). Zur Theorie der Gesellschaftsspiele. Mathematische Annalen, 100(1), 295-320.

Wang, J. (2011). Research on the application of game tree heuristic search algorithm in the game of Gomoku. Science and Technology Information Development and Economy, 21(29), 138-140.

Wang, L. (2018). Optimization research of value neural networks in computer Go (Master's thesis, Beijing University of Posts and Telecommunications).

Yue, J., & Feng, S. (2009). The application of game tree search algorithm in Chinese chess. Computer Systems Applications, (9).