Framework Research on Intelligent Computer Go Game Algorithm Optimization based on Monte Carlo Method

Wei Qiu

Department of Computer Science & Engineering, Langfang Polytechnic Institute, Langfang 065000, China

Abstract

With the continuous development of information technology, the superiority displayed by artificial intelligence has won more and more people’s attention. The intelligent computer game is a key direction of artificial intelligent research, especially the go game, as the world most board game, the knowledge rule of which is hard to be concluded, and is of wide search space that can effectively verify the development level of artificial intelligence. Therefore, it is of vital significance to promote the development of artificial intelligence and computer by using the intelligence computer to play the go game. The Monte Carlo Method is not the name of an algorithm, but the collective name of a kind of algorithms finding the optimal solution. The Monte Carlo Method is widely used in the intelligent-computer go game, which has increased the go game level of artificial intelligent greatly and become one of the best algorithm among artificial-intelligent go game. However, the Monte Carlo Method and its supporting upper-limit confidence-boundary utility tree algorithm are still subject to certain defects; therefore the Thesis is the optimization design of intelligent-computer go game algorithm based on the Monte Carlo Method, which can increase the intelligent-computer go game level effectively, and can also provide experiences and reference for the development of artificial intelligence.

Keywords: Monte Carlo Method, Intelligent Computer, Go Game.

1. RESEARCH OVERVIEW

1.1 Research background

Artificial intelligence is the emerging intelligent machine which can simulate human’s consciousness and thought and make corresponding response through the information technology. The core idea of artificial intelligence is to explore the essence of intelligence, and to achieve the quantitative production on such intelligence; artificial intelligence is likely to surpass human being’s intelligence comprehensively under the background of continuous development of science and technology; the intellectualization has become the key direction of science and technology development. Our country pays high attention to the construction of artificial intelligence, and also proposes that to build up the artificial intelligence industry with value above USD 150 billion by 2030, which reflects that the artificial intelligence has become the key strategy direction of our nation’s development. The term “game” initially means playing chess, then it means the process in which two or more intelligent individuals or teams make decisions and act on their own to get a return or loss under the restriction of certain environment or conditions. The game is common in human’s society; it occurs when any interest conflicts exist among individuals involved. The content of main research on computer game is to achieve independent calculation and decision through the program so as to create game objects like human beings. Chess and cards games can reflect the intelligent level of individuals intuitively, which are key research objects of computer game. Among which, as the world most complicate board game, the go game can be used to verify the intelligence level of computer game effectively. Therefore, it has won wide attention in the industry, and how to improve the go game level of intelligence computer has become the key problem in the development of artificial intelligence filed.

1.2 Literature review

The intelligence computer game is originated in 1968, which was developed and complied by Albert Zobrist during his study of PHD. The function is used to access the go game, which also is used to analyze the rob rules. The period from 1968 to 2005 is usually called as the times of traditional computer go game. During this period an obvious problem existed in computer game, which was the relatively poor computing power of the computer.
game due to the limited computer performance and insufficient resources. What’s more, the ongoing search was interrupted, which made the original intelligent-computer go game program was implemented with an expert system method. The most representative program in the traditional intelligent computer games is the “Hand Talk” and foreign open-source code program GNU Go (Wang et al., 2015) complied by Doctor Chen Zhixing. In 2006, the Hungarian scientist proposed the upper-limit confidence-boundary utility-tree algorithm after the long-term research, which made the Monte Carlo Method could be widely to the intelligence computer game. In the same year, a French team duly developed the new intelligence computer game program – Mogo based on the upper-limit confidence-boundary utility-tree algorithm. Compared with traditional intelligent computer game algorithm, the Monte Carlo Method and upper-limit confidence-boundary utility-tree algorithm have obvious advantages. In addition, as for the Monte Carlo Tree Search Algorithm generated by combining these two methods, the function of which is being perfected continuously; and the level of intelligent computer game and artificial intelligence are in the high-speed development process (Liu, 2011). The intelligent computer game is an artificial intelligent project widely regarded in our nation and even the entire world, and also one of key points of experts and scholars’ research. The International Computer Games Association (ICGA) organizes the intelligent computer game competition and relevant seminars in different places each year; with more than 60 years’ development and contemporary studies, experts and scholars hold the common view that the artificial intelligence developed based on mere simulation of human being’s thought is subject to certain limits; if the method of combining program calculation and filed knowledge is used, the calculation level of artificial intelligence will be increased much effectively, which is the optimized strategy for artificial intelligence game (Liu, 2011).

2. OVERVIEW ON INTELLIGENT COMPUTER GO GAME

2.1 Go game overview

The go game is originated in China, which was created by Monarch Yao, and was spread to East Asian countries in Sui and Tang dynasties; now it is popular in China, Japan South Korea and North Korea; and the influence of go game in European and American countries is also increasing. Especially in the intelligent computer go game, the go game has won wide attention from all parts of the society (Li et al., 2012). The chessboard of go game is shown in Figure 1:

![Figure 1. Go Chessboard](image)

The go chessboard is easier, which consists of 19 vertical and horizontal lines. There are 361 intersections are available. The go game position consists of two subjects, the black chess pieces for one side, and white chess pieces for the other side. The black chess pieces go first, and one piece can put down for each round; in case the calculation is implemented when one side gives up or both sides agree, the winner is decided based on the area size taken by both sides (Li et al., 2012).
2.2 Calculation complexity of go game

2.2.1 Space complexity of go game

There are 19 vertical and horizontal lines in the go chessboard, and 361 intersections in total; among which, each intersection may be subject to three states: black piece, white piece or none. Therefore, there are $3^{361}$ changes in the go chessboard. The scientific notation is applied to get the conclusion that the space complexity of the go chessboard is $1.74 \times 10^{172}$. However, due to the influence of factors such as go game rules etc. in the actual game, a crop of unreasonable or repetitive problems are included in the conclusion of $1.74 \times 10^{172}$ (Lv Gong, 2012). Therefore, the $1.74 \times 10^{172}$ is only the upper limit of space complexity of go chessboard abstractly. However, as such unreasonable or repetitive problems are rare, even the value is smaller than $1.74 \times 10^{172}$, the order of magnitudes is still very huge. The domestic and foreign relevant researches indicate that the space complexity of go chessboard is $2.089 \times 10^{170}$.

2.2.2 Game tree complexity of the go game

There is a saying in the go game – “There is no the same chess situation forever.”, which means that the go game is of high complexity; the totally same chess situation did not occur in the past, neither in the future (Liu et al., 2016). Such opinion is of relative absolutization, but the same chess situation did not occur in thousand year’s development history, which indicates the high complexity of go game art. Generally speaking, the complexity of the game tress is much higher than the space complexity. As it is referred above, the space complexity of the go chessboard can reach $2.089 \times 10^{170}$, but the complexity of its game tress can even be hardly calculated, only the rough estimation can be achieved. According various chess situations in the past and contemporary China and foreign countries, the average move number of a round of go game can be calculated, which is the height of game tree; and each move is subject to different choices, and these choices are the branches of the game tree. Assume that 150 moves are required to complete a round of go game, then each move is subject to 250 choices, based on which the complexity of the go game tress can be estimated as about $10^{360}$ (Zhang, 2016).

2.2.3 Horizontal comparison of go game complexity

Nowadays, many international famous board games have gone through the research on artificial intelligence game; the horizontal comparison of space complexity and game tree complexity of each kind of board game can be achieved by referring to relevant data. The horizontal comparison of go game complexity is shown in Table 1:

<table>
<thead>
<tr>
<th>type</th>
<th>Space complexity (10 log)</th>
<th>Game tree complexity (10 log)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Draughts (100)</td>
<td>30</td>
<td>54</td>
</tr>
<tr>
<td>Heks (11 x 11)</td>
<td>57</td>
<td>98</td>
</tr>
<tr>
<td>Chess</td>
<td>46</td>
<td>123</td>
</tr>
<tr>
<td>Chinese chess</td>
<td>48</td>
<td>150</td>
</tr>
<tr>
<td>Amazon (10 x 10)</td>
<td>40</td>
<td>212</td>
</tr>
<tr>
<td>a chess-like game</td>
<td>71</td>
<td>226</td>
</tr>
<tr>
<td>connect6</td>
<td>172</td>
<td>140</td>
</tr>
<tr>
<td>The game of go (19 x 19)</td>
<td>172</td>
<td>360</td>
</tr>
</tbody>
</table>

The Table 1 is list of eight world famous board games, including the Draughts, Hex (11 x 11), chess, Chinese Chess, Amazon (10x10), Mini Shogi, Connect 6 and go game (19x19) etc. Among which, the space complexity and game-tree complexity of the chess is much higher than other board games. Therefore, except chess items designed specially, the chess has become the game item with the highest complexity developed by human beings.
3. BOARD ASSESSMENT FOR INTELLIGENT COMPUTER GO GAME

3.1 Static board assessment

The game tree complexity of the go game can reach $10^{360}$, and as the duration of each move is limited, therefore, the deeper search can be hardly deployed. However, if the board assessment can be applied to the accurate assessment of certain states, good game effect can be achieved without deeper search. This method is highly depending on human beings’ thought and intelligence, and the intelligent computer can be only used to process some problems of high complexity which can only be solved by experts by simulating experts’ thought pattern based on human experts’ knowledge. Therefore, this pattern is also named expert system, which is the algorithmic system widely used in traditional intelligent computers. The expert system is of high superiority; however, it is still subject to many defects on many problems due to the restriction of its own conditions. If these restraining factors can be solved under the continuous development of science and technology, and expert system can still make great contributions.

3.1.1 Evaluation function

The static board assessment is a kind of expert system essentially, which is calculated and assessed by combining the calculation of intelligent program and filed knowledge. Therefore, if the more accurate conclusion is to be made under this pattern, the solid filed knowledge must be equipped. However, as for the go game, some important problems such as the connection and regional attribution division of chess pieces etc. can be hardly presented in the static board assessment, the optimization should be made to traditional methods. The key algorithm of static board assessment is the block combination; due to the high complexity of go game, if each move is calculated from the overall angle, then massive amount of calculation content will be generated. However, as any single entity is composed of countless pats, even the Kudan chess player with rich experience can only subdivide the entire board for processing so as to make targeted judgement. The block selected by the chess player must be of certain salient features, therefore, the combination of such features can make more accurate block for calculation selected by the expert system. There are two branches in block combination, as shown in the following:

Firstly, consideration in global perspective. The entire chessboard should be subject to the subdivision processing before the block assessment, then different indexes of block assessment should be integrated so as to get the assessment value of different blocks; and the block selection is made against assessment values, the formula is shown as below:

$$Eval(board) = \sum_{i=0}^{N} a_i \times Eval(P_i)$$

(1)

Where, $a_i$ means the weighted value of different blocks, which is the value of intersections included in the block and the total number of intersections.

Secondly, consideration in block perspective. Each block should be distinguished after different blocks are divided. Firstly, the feature differences of different blocks should be listed, then the significance proportion of each feature should be graded. Then the importance of different block features should be subject to the value assessment; as the features of go game is relatively rare, therefore, different features will be subject assignment with the method of selecting each professional chess player’s data manually so as to ensure the accuracy of value assessment, the formula is shown as below:

$$Eval(part) = \sum_{i=0}^{N} a_i \times f_i$$

(2)

Where, $a_i$ represents the weighted value of each feature; the weighted value is subject to the assignment implemented by analyzing the professional chess player’s data (Zheng et al., 2016).

4. INTELLIGENT-COMPUTER GO GAME BASED ON MONTE CARLO METHOD

4.1 Monte Carlo intelligent-game model
The Monte Carlo Method is one of key algorithms in intelligent computer go game, and also the major method used in modern computer game. The intelligent game flow of Monte Carlo Method is shown in Figure 2:

![Figure 2. The Intelligent Chess Game Flow of Monte Carlo Method](image)

The Monte Carlo Method is used to make intelligent computer game, which is to randomly select one point for test from all right move destinations on current chessboard essentially; it is the process of continuous repeat random selection until the game is finished; then the final result should be analyzed and the decision should be made by returning to current situation. The result selected in one time randomly with this method is much reasonable than the selection made before, which is the method used to look for optimal solution (Wang et al., 2016). According to the analysis on the flow chart, the decision-making time is checked when the decision is started to be made; if the time is still insufficient, a new move destination will be selected randomly under the move destination selected currently; and the test will be implemented too verify the rationality of this destination, and the winner will be decided based on Monte Carlo assessment, and the move visit times and result will be updated. If this move destination is not available, then a new move destination will be selected randomly. When the decision-making time is up, the most reasonable move destination will be selected with the Monte Carlo Method based on current result; although this method cannot be used to ensure the best result, it can ensure that maximum attempts can be implemented within the limited decision-making time so as to ensure the rationality of the result (Hu et al., 2014).

4.2 Optimization methods for intelligent computer game

4.2.1 Multi-arm bandit model

Multi-arm bandit model is the classical statistical model, and also the optimum decision model; the essential thought of which is to update the result continuously so as to get the more optimal result (Zhou et al., 2015). The advantage of multi-arm bandit model is that the knowledge can be acquired through independent experiment and exploration without the filed knowledge, so that the knowledge can be updated continuously and the more optimal decision can be achieved. Multi-arm bandit model is decided by large amount of discrete-type random variables \( X_{i,n} \) \((1 \leq i \leq K, n \geq 1)\), where, \( i \) represents one decision factor, and \( n \) represents the decision-making times of decision factor \( i \) (Li et al., 2014). One decision factor is used to make decision, and the incomes are \( x_{i,1}, x_{i,2}, \ldots \), these incomes are decided by the uncertain expectation \( \mu_i \). In the meanwhile, the incomes generated are independent to each other among different decision factors, which means that different \( x_{i,s} \) and \( x_{j,t} \) will occur for each \( 1 \leq i \leq k \) and \( s, t \geq 1 \) (Liang et al., 2015). The optimum solution formula of multi-arm bandit model is as follows:
\[ c_n = j, \mu_j = \max_{1 \leq i \leq k} \mu_i \] (3)

4.2.2 Upper-limit confidence boundary strategy

The upper-limit confidence boundary strategy and the Monte Carlo Method are the same; they do not refer to one algorithm, but the joint name of a kind of algorithms; the upper-limit confidence boundary strategy is the algorithm collection which can solve the multi-arm bandit model problems effectively. In which, UCBI algorithm is the basic algorithm of upper-limit confidence boundary strategy, the formula for indexes \( I_j \) of which is as follows:

\[ I_j = \bar{X}_j \sqrt{\frac{2 \ln n}{T_j(n)}} \] (4)

From the practical point of view, the upper-limit confidence boundary strategy can be used to promote the computer game level effectively, to optimize the Monte Carlo Method and is of crucial significance to the overall development of artificial intelligence (Xu and Wang, 2016).

REFERENCES

Liu Y.J. (2011), The main technical analysis of the six chess game in computer game, Computer knowledge and technology, 7 (10), 2310-2312.