Ascertaining the Play Outcome using the Single Conspiracy Number in GoBang*

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***Abstract*—Analyzing the effect of value change in the MIN/-MAX search algorithm towards gameplay can be challenging. The single conspiracy number (SCN) is an indicator that can reflect such information. In this paper, SCN is utilized to identify different factors and analyze patterns that influenced a 5-in-a-row game called GoBang. SCN values from various GoBang games were calculated and analyzed. A specific GoBang dataset called the "chess manuals" is used as the simulation test-bed to reflect real game situations. Results show that such a method is proven to indicate different game situations, leading to the ability to ascertain the outcome of the play, given the right threshold, relative to the MIN/MAX evaluation value.**

***Index Terms*—Artificial intelligence, game-theoretic value, GoBang, tree-based search, single conspiracy number**

I. Introduction

Analyzing the information of the game progress provides a significant advantage (e.g., the difficulty of such a process). Single conspiracy number (SCN) [1] is a variation of two well-known classical algorithms, the conspiracy number search (CNS) [2] and the proof number search (PNS) [3]. One of its proposed usages is to evaluate the difficulty of the current state of the game of getting the MIN/MAX value over the specified threshold point.

The SCN works as an indicator that can show the state of the game directly. Although the classical algorithms may realize such a game state to some extent, it is challenging for researchers to analyze the board game's statistical regularity through the value of nodes alone. However, by putting forward a benchmark value, namely the *threshold* (denoted as T), the SCN value will show the difficulty of obtaining such threshold value; thus, provide utility for analyzing and predicting the outcome of the game.

The game of GoBang is a "Five-in-a-row" game, in which players need to have five of their pieces to line up horizontally, vertically, or diagonally to win the game. GoBang is one of the most popular and strategic board games in the world. This paper aims to employ SCN in GoBang and determine its ability to indicate the game state and its difficulty.

II. Related Game-Tree Search Algorithms

MIN/MAX search algorithm is the origin of all the variants of game-tree search in games [4]. It has been applied to all kinds of perfect-information games such as Checkers, Go, and Chess. The core idea of the MIN/MAX search algorithm is changing the selection criteria of the calculated layers (MAX is the player's side, and MIN is the opponent) during the search process. Each player selects the node with the most advantageous value in each layer as the primary goal.

In complex games (e.g., Chess and Go), the number of tree nodes would explode as the game progresses. The most commonly used method to reduce computational cost and time involves optimization procedure that prunes less significant branches of the search, such as the $\alpha\beta$ procedure, where the value of the current node is compared with the node to be calculated, accelerating the speed of the game-tree search. The $\alpha\beta$ procedure is shown to be optimal in a certain sense, and bounds are obtained for its running time with various kinds of random test data [5].

Among the variants of MIN/MAX search algorithms, two of the search algorithms, the conspiracy number search (CNS) and proof number search (PNS), had profoundly influenced the development of game programming. The CNS selectively expands game-tree nodes until a specified degree of confidence is achieved in the root in a MIN/MAX tree search algorithm [6]. CNS has been incorporated to create a strong program but suffers from low search efficiency because of its slow convergence and expensive computing conspiracy numbers. Meanwhile, the PNS, inspired by the concept of CNS, is an efficient AND/OR tree search algorithm for solving complex endgame positions by establishing the game-theoretical value in a best-first manner [6].

However, both CNS and PNS cannot measure the current state of the game from a node value due to a lack of a perspicuous indicator. The single conspiracy number (SCN) algorithm was proposed [6] to address such a problem. Inspired from CNS and PNS, the single conspiracy number (SCN) is an indicator that estimates the difficulty of the current game state to get a value of MIN/MAX tree search more than a predefined threshold [1] [6] [7]. SCN is a framework-dependent analytic method that relies on the framework of its implementation. In this case, SCN depends on the evaluation function used to evaluate the M value of a position in a game.

Using SCN in Chinese Chess had proven to be a useful measure of stability in the game progress pattern [1]. The SCN value of a position is compared to its heuristic value based on the $\alpha\beta$ framework. The comparison result shows that SCN

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is a better measure to show the difficulty of a position than heuristic value. Another application of SCN was in Checkers [7]. It was found that it can distinguish both the difficulties of the current game state and the states that constitute good and bad games. Based on these applications, given the heuristic value of a framework, SCN can increase the understanding of which factor and play pattern that influenced the result in a 5-in-a-row game. In other words, this research is utilizing SCN to ascertain the outcome of a play.

III. Single Conspiracy Number Analysis in GoBang

A. Brief Introduction of GoBang

Gobang is a k-in-a-row game and a part of 15,15,5-game with added rules to maintain fairness. Solving a 5-in-a-row game with various board sizes shows that the larger the board is, the more advantageous it is for the first player. This situation is likely because as the board size increases, the first player's strategies also increase [8].

In GoBang, the players play their pieces (black or white) one by one to advance the game. The condition for victory is by making one's pieces to form the "five-in-a-row" either horizontally, vertically, or diagonally[1]. So, when the black player tries to connect his pieces into a line, his opponent (white) needs to attack by linking his white pieces by cutting down the potential threat of the black pieces. It is worth noting that, compared to a similarly played game (e.g., Gomoku), both GoBang and Gomoku try to form pieces of "five-in-a-row," and black starts first. However, pieces placed by the players in GoBang can be removed by surrounding two neighboring opponent's pieces by their pieces.

To this end, the reason for choosing GoBang in this paper is twofold. Firstly, GoBang is a unique game in which it has simple rules but a huge state space. Its state space is estimated to be 10^{105} [9]. Understanding the information progress of such a game will be a powerful tool for game analysis. Secondly, SCN search performance is likely to be better in a tactical game such as GoBang.

B. Finding Single Conspiracy Number

In a tree-based MIN/MAX search algorithm, much bigger node value ensures the player's victory. SCN indicates the difficulty of a node getting to a specific value of T, which in this context, should reach near ∞ when it is easier to reach T. This definition is then used to evaluate a node: if the node value is bigger (smaller) than T, the node corresponds to *superiority* (*inferiority*) since it behaves better than expected (fall short).

There are two main reasons for applying the SCN. First, the value of the SCN calculation is independent of the MIN/MAX value calculation. Second, the SCN works similarly to the CNS and PNS, making it an easily adopted in the MIN/MAX tree framework. Let $n.scn$ be the SCN of a node n and M be the MIN/MAX value of node n, whereas T is the threshold of the legal MIN/MAX values. The formulation of the SCN is given as follows:

- When n is a terminal node
  - If $M \geq T,$ then $n.scn = 0$
  - If $M < T,$ then $n.scn = \infty$
- When n is a leaf node (not terminal)
  - If $M \geq T,$ then $n.scn = 0$
  - If $M < T,$ then $n.scn = 1$
- When n is an internal node
  - If n is a MAX node: $n.scn = \min_{n_c child\, of\, n} n.scn$
  - If n is a MIN node: $n.scn = \sum_{n_c child\, of\, n} n.scn$

C. Experiment Design

An experiment to observe the game progress of GoBang was conducted through authoritative data and the GoBang program that calculates both the MIN/MAX value and SCN value. In GoBang, there exist a collection of data that is called "chess manual" which recorded the game scores of various games play competitions that range from the world level to the national level. Each chess manual comprises multiple data from various games, in which one data contains a game score from a match, complete with every player's moves. Each move is defined as one-ply in this experiment. The chess manuals for this experiment were downloaded from a professional GoBang website [10].

In this experiment, a GoBang program with SCN is specifically developed using Python programming language to analyze the moves made by the GoBang player in 20 matches data from the "chess manual". The data taken were varied in length, with the shortest being ten plies while the longest game being 71 plies. The program assigns scores based on the game state's patterns as an evaluation function for the MIN/MAX algorithm. The evaluation function is looking for the players' longest line in the board. If a player has more continuous pieces, their score will be higher. The evaluation function in this case ignores the opponent continuous pieces as to not affect the M value calculated. This value is then used to represent the M value of the player in the SCN evaluation. The resulted score from both players is then calculated based on (1) (see Section IV-A).

The GoBang program must consider searching an enormous number of nodes of the tree-based search framework (up to 10^{16} or more), which may induce very high computational cost and time. Typical techniques of addressing such issues include pruning unnecessary nodes and fast evaluation of nodes using the heuristic and evaluation method, respectively. In this paper, a transposition table is used to identify line of five GoBang pieces which significantly expedites the search evaluation.

IV. Experimental Results and Discussion

A. Process Analysis

The game process analysis is conducted by observing the changes of MIN/MAX value (denoted as M) and SCN value through the GoBang game progress. The search depth and the threshold is set to a fixed value ($D = 4$ and $T = 8000$) in order

[1] https://www.yucata.de/en/Rules/Gomoku

to reduce computational cost and indicates an advantageous situation, respectively[2]. The evaluation function for the victory position is set to an extremely high value (i.e., "line five" is 1000000).

In GoBang, any player may attack or defend at any stage of the game. It is important to determine the value of a specific board position based on the value of M and the adopted evaluation function. Therefore, the M is calculated based on (1). The M_{myside} is MIN/MAX value of the player and M_{enemy} is MIN/MAX value of the opponent. The e is a weight coefficient used to show the significance of a piece to the enemy (in this experiment, $e = 0.5$).

$$M = M_{myside} + e \cdot M_{enemy} \tag{1}$$

Figure 1(a) shows the trend of the MIN/MAX values (denoted as M) of the winner through the game, whereas the winning step was excluded due to extremely high value. In general, the M is an upward trend, which rises along with the growing amount of the game pieces. Also, the trend fluctuates when faced with a complicated situation. Both players attacked and defended all the time, and both two sides try to break a deadlock and become the victor by gaining a "line five". This situation leads to the positive and negative "swings" of the M values throughout the game progress.

Figure 1(a) also shows the trend of SCN value for the winning player, which is in agreement with the regulation of M variation. A sharp decline in SCN always happens when rapid growth occurred in M value. For example, such a situation can be observed at ply $13-14$ or ply $18-19$. Recall that low SCN corresponds to "behaves better than expected". Concerning the rules of GoBang, decreasing SCN equals to a favorable condition since the pieces can have a longer and closer connection. Thus, it can be inferred that high SCN indicates that the players' pieces on the board are more dispersed and less chance to line their pieces.

Figure 1(b) and Figure 1(c) show the trends of SCN values compared between players, demonstrating the contrasting or similarity among them. When in the opposing trends (ply $14-15$ in Figure 1(b) or ply $19-23$ in Figure 1(c)), the situation of the game has justified that the player with low SCN value controlled the game while the player with high SCN value tried to defend it. In contrast, a similar value of SCN appeared on both players based on two occasions. First, the values of SCN from both sides are almost the same because there are few pieces on the board (Figure 1(b)). Second, in the late-game stage (i.e., after ply 19 in Figure 1(b) or after ply 23 in Figure 1(c)), the values of SCN of both players are approaching zero. Such situations were because the game achieved complex states where determining the dominating player is difficult.

Observing from the standpoint of T value as the evaluation criterion, a low T value indicates that the requirement is easy to meet since M can exceed T. Meanwhile, a high T value indicates a formidable challenge to be overcome since M is unable to exceed T. Another experiment is conducted where the T value is set to 2000, 5000, and 8000, to indicate the possibility of achieving "line two", "line three" and "line four", respectively. The influence of T to the SCN values is portrayed in Figure 2.

Based on the Figure 2, along the increasing M value, a lower T value is the least reliable when approaching mid- to late-game stages. For instance, $T = 2000$ makes the SCN values close to zero after the seventh ply, making it difficult to determine the game progression of the mid- and late-game stages. On the contrary, the value of $T = 5000$ or $T = 8000$ behaved better in the sense that the dividing line between the mid- and late-game stages were identified at ply 19. Since "line three" is viewed as an easily achievable state of GoBang game, the best choice for threshold T is 8000.

B. Discussion

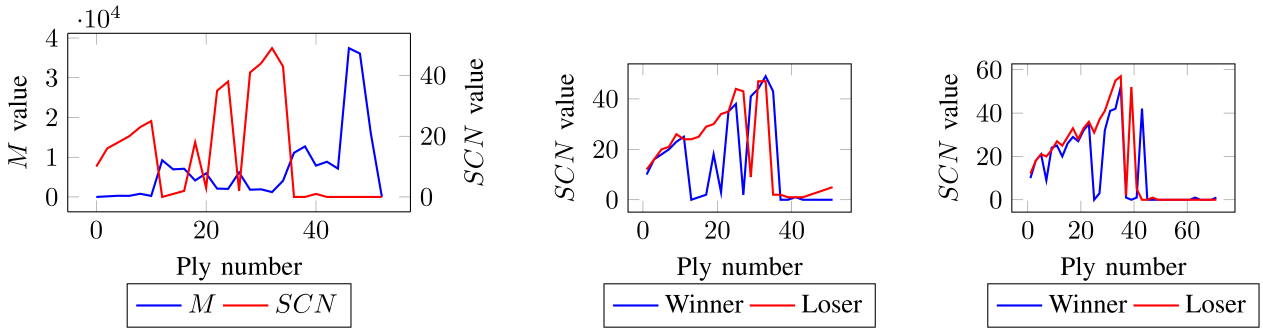
In this experiment, the SCN value is derived not only from the players' current state but also from the opponent state. Because of the nature of the game, any player may attack or defend in one game state. With the adopted evaluation function, SCN can be used to ascertain and observe such progress in the GoBang game.

In general, different SCN values indicate a different game situation. Low SCN value has been shown to imply a favorable progression of the game, where a player reached game conditions that considered advantageous compared to its opponent. This situation implies better options for longer and closer connections between its pieces. In contrast, high SCN value indicates adverse game progression, where the game conditions are far from reaching the goal state (nonexistence of connected pieces).

It is worth noting that analyzing the SCN values has to be made in response to the opponent's side. When one player has low SCN value, while another has a high SCN value, the player with high SCN value typically implies defensive or conservative play. They tend to focus on blocking their opponent rather than creating a line five. When the values of SCN of both players are approximately similar and higher than zero, the game state reaches a situation that roughly translated as "stalemate" or "neutral." However, when the values of SCN of both players are approaching zero, the game state reaches a complicated situation where determining the game's dominant player is challenging.

Concerning the threshold value (T), a low value of T makes MIN/MAX value (M) to exceed it easily. A high T means overcoming it becomes difficult since $M \leq T$ is always right. In a sense, the T values showed the "degree of freedom" in term of the informational aspect of the game, where the low value of T (< 5000) causes the SCN values to be close to zero in early stages of the game, whereas a higher value of T (≥ 5000) provides definite bounds of the mid- and late-game stages. However, these values of T are highly dependent on the evaluation function used in the game. Its value is bounded by

[2] $T = 8000$ stands for situations of single "line four" or some of "line three" pattern of GoBang existed, and the player is advantageous where it is not possible to indicate the leading status of the player when $T < 8000$.



(a) Value trend of minimax and SCN (b) An example of SCN compared (c) Another example of SCN compared

Fig. 1. Cases of SCN indicator

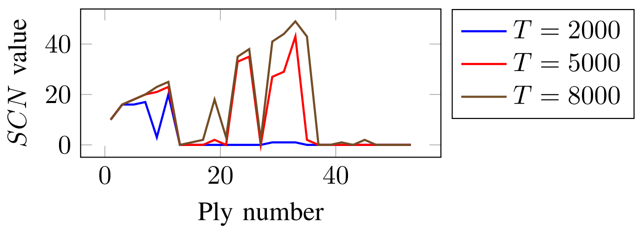


Fig. 2. Influence of threshold T to the SCN values

the minimum and maximum value that can be returned by the evaluation function. Thus, it is essential to distinguish which value of T should be considered as high or low. In essence, considering the appropriate T value is crucial for portraying the SCN values.

The result from this experiment shows that SCN can indicate different game situations as well as the change of play pattern that caused or precede it. It can also distinguish each player's play pattern by applying it to moves taken by the player only. Towards the end of the game, the stabilization of the SCN value indicates the outcome of the game several steps prior. These show that the game result can be ascertained and described through a single indicator.

V. Conclusion

The single conspiracy number (SCN) was utilized in this paper to analyze the game progress of each player in a popular board game called GoBang. By observing the progress of SCN value in the GoBang game, the observer can ascertain the current condition of the game, whether it is favorable or unfavorable. It can also show the current progress of the game, whether the game is ending soon and results in a win for the favored player, or there is a chance for the disadvantaged player to continue the game and change their condition.

For a specific game state in GoBang, comparing the SCN trend of the winner and the loser also shows the game current situation, in which when the SCN curves of the players have an opposing trend, it means that one player currently being defensive, while both players having similar trend means that the game is currently at "stalemate" or "neutral". Besides, the threshold (T) selection affects the SCN curve, where low T always resulted in lower SCN value, which leads to a conclusion that higher T, relative to M value, can reflect the game situation better.

Future works can be focused on expanding the potential of indicating the play pattern based on the SCN values in a generalized k-in-a-row game as well as its implementation into continuous and score-based games, such as sports games (i.e., soccer, basketball). Implementation of SCN in games with different play patterns can also help create an opponent player model in GoBang. From another perspective, online implementation of SCN and its usage in critical strategic and tactical decision making in the various game may provide valuable advancement in terms of its roles as a search indicator. Further works can focus on pattern analysis and inclusion of factors that can profoundly affect the game, such as experienced players, number of shots, or teamwork, which depends on the characteristic of the play.

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