

Trend Oriented Opening Book Construction

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Abstract:

In contrast to the other two phases of the game, methods for constructing opening books are less investigated. Since the playing strengths of state-of-the-art programs are really close to each other, more often than not, the results may be decided by the quality of the opening book. Therefore, the importance and demand for good quality opening books are on the rise. In this research, we propose an active opening book construction method that takes the trend of the evaluation values into account, rather than depending solely on the evaluation value itself. We argue that the variation of the trend is more suited to reflect strategic properties of an opening line, since the objective of the opening phase in a game is to achieve a strategic desirable position. We will apply the proposed method to the game of Othello, demonstrating its characteristics and performance.

1. Introduction

Most traditional board games, such as Chess, Shogi, and Othello, can be divided into three phases, namely the opening, the middlegame, and the endgame. Search algorithms with heuristic enhancements, such as $\alpha\beta$ -search or Monte-Carlo tree search (MCTS), are applied throughout a game. In addition, according to the characteristics of the different phases in a game, various methods are applied to improve the performance. For the endgame, databases, which store pre-calculated endgame positions (with win/loss information) obtained by retrograde analysis, are commonly applied. A similar approach is also available for the opening phase of the game.

An opening book is a database which stores the pre-calculated values of the moves that are likely to occur in the opening phase of a game. The purpose of an opening book is not only to save computation time, but also to improve the quality of the moves played in the opening phase, since the search depth used for pre-calculation is deeper than the search performed during play.

The objective of the opening is to achieve a strategically desirable position, and strategic advantages are effectively long term advantages. Long term advantages could be deceptive, as it may seem like a blunder in the short run. An example is the gambit plays in Chess, where the sacrifice of pieces would seem to be a bad move at first, but later prove

to be advantageous.

The identification of such strategic moves can be performed by observing the trend of evaluation values, i.e., the change in the evaluation value, as the game progresses. This can often be observed in games where one player accumulates his or her advantage gradually, which in turn translates to the gradual increase of the evaluation value. Long term traps can also be observed where there will be a deflection in the trend of the evaluation value. Such identification would be computationally costly, and thus would not be practical to perform it in play. Hence it would be better to be identified beforehand, and stored in the opening book.

In this research, we propose an active opening book construction method that takes the trend of the evaluation values into account, rather than depending solely on the evaluation value itself. We argue that the variation of the trend be more suited to reflect strategic properties of an opening line, since the objective of the opening phase in a game is to achieve a strategic desirable position. We will apply the proposed method to construct an opening book for the game of Othello, and demonstrate its characteristics and the performance of the constructed opening books.

2. Related Work

Today, most of the state-of-art programs have opening books, and there is a wide range of methods for constructing these databases. There are two major approaches for opening book construction.

The first approach is *passive book construction*, in which the opening book is first constructed manually by experts or compiled from game records, and later verified or extended according to the results of later game play [1][2]. The main advantage of this approach is that it avoids los-

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Construction Algorithm	Expansion Policy	Evaluation Method
Best-First[3]	Best-First	Minimax-based Search
Drop-out [4]	Drop-out	Minimax-based Search
Stage-wise Strategy [5]	Uniform Expansion	Monte-Carlo Tree Search
Quasi Best-First [6]	Quasi Best-First	Monte-Carlo Tree Search
Beta Distribution Sampling [6]	Beta Distribution Sampling	Monte-Carlo Tree Search
UCT-based [7]	Monte-Carlo Tree Search	Shallow UCT

Table 1 The performance of the *Detailed Trend* opening book versus the *Baseline* opening book. The drop out column shows the depth which the Othello playing program drops out of the *Detailed Trend* opening book. The result column shows winner, and the score of the game.

ing in the same way, in a previously encountered opening. Also, it can take the advantage of human expert knowledge, which can be very valuable in identifying the strategic properties in the opening phase of the game. The major disadvantage is that they require a sufficient number of good quality game records, or access to a human expert, which may not be easily obtained.

The other approach is *active book construction*. In this approach, the opening book is mainly constructed and expanded automatically. The major advantage of this approach is that it does not necessarily need a huge number of game records for construction. Therefore, they can be used for a wider range of games than passive book construction, especially for the games that are not extensively studied theoretically, or does not have a huge number of game records. Another advantage is that they allow the game-playing program to provide input to the construction process, thus the constructed opening book may be more suited to the characteristics of the game-playing program.

The process of active book construction is very similar to that of the process of a typical tree search. The active book construction process essentially consists of two major parts. The first part is the *expansion policy*, which decides the set of nodes in the game tree that are needed to be explored and expanded. The second part is the *evaluation method*. The evaluation method not only gives an evaluation value to the node in question, but provide feedbacks to the expansion policy, which is essential in the expansion decisions.

A number of active book construction method has been proposed, and there two major categories. The *minimax-based approaches* [3][4] assumes that the move which strong program makes are essentially good moves, thus the expansion policy focuses on expanding the nodes that has high evaluation value. The Minimax-based approaches applies a evaluation function or minimax-based search methods, such as $\alpha\beta$ -search, as the evaluation method.

However, the opening books constructed by the minimax-based approaches performs poorly with Monte Carlo Tree Search-based game-playing programs. Therefore, *Monte Carlo Tree Search-based approaches* [5][6][7] are recently proposed to construct opening books that are more suited to the playing style of the Monte Carlo Tree Search-based game-playing programs. A summary of active book construction methods is given in Table 1.

3. Proposed Method

In this section, we will first consider what is our primary objective in constructing opening books. Next, we will introduce the expansion algorithm for our opening book construction. Finally, we will introduce the criterion that we have considered in our expansion policy.

3.1 The Objective of Opening Book Construction

The main objective of the opening phase of a game is to achieve a strategically satisfiable position, that is one has the advantage, or at least has no major disadvantage when the opening phase of the game is over. But when a player is preparing his or her opening repertoire, apart from the absolute strategic value of an opening, whether or not the player in question is comfortable with the resulting position is also important. That is, whether or not the player is able to take the right action might be a more critical criterion. Even if the resulting position is a theoretically winning, if the player does not understand the position and fails to exploit the advantage, the opening line is still of no use to the player.

The same argument applies for opening books for game-playing programs. In a lot of games, such as Chess, most of the opening books are constructed by experts or from expert game records. Due to different properties and characteristics of the programs, there are situations which an opening play is considered to be advantageous, but the program fails to exploit.

Therefore, an ideal property is that *when the game-playing program "drops out" of the opening book, the resulting position should be a position which the game-playing program can correctly choose the subsequent actions*. Constructing an opening book that has such a property should be the main objective for opening book construction.

We aim to achieve this objective by determining whether or not a certain opening has a certain strategic property, and assessing whether or not the game-playing program can handle the position if the game progresses by observing the trend of evaluation values.

3.2 The Expansion Algorithm

The major difference between the search problem and opening book construction is that the objective of the search

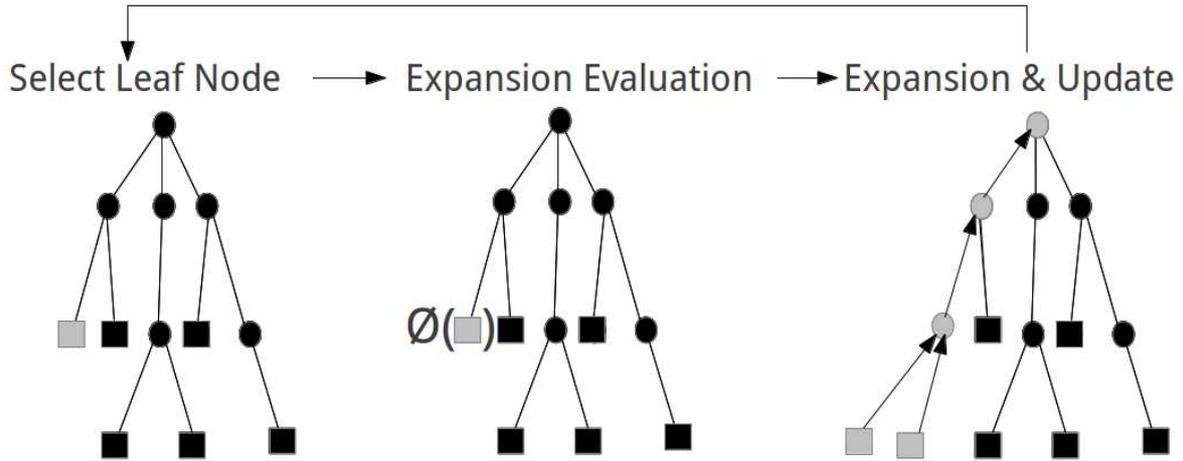


Fig. 1 The expansion process mainly consists of three steps: select leaf node, expansion evaluation, and expansion & update. The squared nodes are the leaf nodes, and the circle nodes are interior nodes. The nodes in grey are the focus in the particular stage in the process. The first step is the selection of a potential candidate node for expansion. The second step is evaluate whether the selected leaf node is needed or worth further exploration. If the result of the expansion evaluation is true, then the node is expanded, and updates will be performed to its ancestor nodes.

problem is to find a single optimal variation, whilst opening book construction aims to include every possible variation that is likely to occur in the opening phase.

The overall process of the algorithm is depicted in Figure 1. The squared nodes are the leaf nodes, and the circle nodes are interior nodes. The nodes in grey are the focus in the particular stage in the process. The expansion process mainly consists of three steps: select leaf node, expansion evaluation, and expansion & update. The first step is the selection of a potential candidate node for expansion. The second step is evaluate whether the selected leaf node is needed or worth further exploration. If the result of the expansion evaluation is true, then the node is expanded, and updates will be performed to its ancestor nodes.

We applied beam search as the main expansion algorithm, since it allows us to explore multiple possible candidate opening plays at the same time. Therefore, every leaf node is a possible candidate for expansion. The proposed construction algorithm is described in Algorithm 1.

At each iteration, the algorithm looks through every child node of the leaf nodes, and evaluates its value. The expansion policy ϕ assesses whether or not the child node should be expanded; if it should be expanded, it is added to the candidate queue. After finishing assessing all the child nodes, the evaluation value and other necessary information of the leaf node and its ancestor nodes will be updated.

3.3 The Expansion Policy

For every candidate expansion node n , a search with iterative deepening to depth d is performed, thereby obtaining a sequence of evaluation values e_0, e_1, \dots, e_d , where e_i is the evaluation value of i th iteration. Therefore, e_d is the evaluation value of n . Let δ_i be defined as $\delta_i = e_i - e_{i-1}$, which is

Algorithm 1 Trend-oriented opening book expansion algorithm

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1: while candidate queue  $C$  is non-empty and there is time left do
2:   for each candidate  $c_i$  in  $C$  do
3:     add  $c_i$  to the opening book  $B$ , expand the leaf nodes of  $c_i$ 
4:     for for each leaf node  $l_j$  of  $c_i$  do
5:       evaluate  $l_j$ 
6:       if  $\phi(l_j)$  is TRUE then
7:         add  $l_j$  to  $C$ 
8:       end if
9:     end for
10:    update  $c_i$  and all its ancestor nodes
11:   end for
12: end while

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the difference between neighbouring evaluation values.

The expansion policy ϕ on the candidate node n is as follows:

- (1) If $e_d > T_h$, where $T_h > 0$ is a given threshold, then ϕ returns FALSE, since there is a huge advantage for the program, it can win on its own.
- (2) If $e_d < T_l$, where $T_l < 0$ is a given threshold, then ϕ returns FALSE, since the disadvantage is too great, thus there is no point in looking on further.
- (3) If $T_l \leq e_d \leq T_h$, then ϕ returns TRUE, if the following conditions are identified:
 - (Accumulative advantage): If there is a steady increase of the evaluation value, which indicate that further advantages may be accumulated as the game progresses, even if the initial evaluation value may not be very high.
 - (Existence of long term trap): If there is a sudden turn in the trend of the evaluation value, it may indicate there may exist a long term strategic trap, and thus

needs further investigation.

Examples of *accumulation advantage* and *existence of long term trap* are given in Figure 2 and Figure 3. The values e_i are the evaluation value of the position when a search is performed to depth i . The values δ_i is the value of the edges between two points, which represents the difference between neighbouring evaluation values.

It can be observed in Figure 2 that although the initial evaluation value e_0 is low, the overall trend is steadily increasing, which may indicate the presence of some kind of long-term strategic advantage.

In Figure 3, it can be observed that although initially the evaluation value is decreasing, the value starts to increase after the point e_4 , which may indicate there is an existence of a long term trap.

In practice, we try to identify the “accumulation advantage” and the “existence of long term trap” by the following criteria:

- **Global trend:** The global trend represents the overall trend in the iteration. If there are more $\delta_i > 0$ than $\delta_i < 0$, then we say the global trend is increasing, and vice versa.
- **Local trend:** The local trend is only observing a part of the δ_i sequence. For example, we may observe only the last two δ_d and δ_{d-1} .

By observing the global trend criteria, we can identify whether or not there exists an “accumulation advantage” or “existence of long term trap”. But by only observing the global trend is not enough to distinguish whether it is an “accumulation advantage” or a “existence of long term trap”.

The local trend criteria can be used to identify specifically which condition it is. If it is “accumulation advantage”, the positive and negative δ_i would be uniformly distributed throughout the whole sequence, whilst “existence of long term trap” would display two major clustering of positive and negative δ_i .

4. Experimental Results

We will analyse the characteristic and the performance of the opening books constructed by our proposed method on the game of Othello in this section. Figure 4 depicts the board and candidate moves for the initial position.

We will start by giving the details of the experimental settings and the constructions of the opening books. Next, a detailed analysis of the opening books will provide an intuitive insight in how the expansion policy effects the shape of the opening book. The performance of the opening books will be given in 3.3.

4.1 The Construction of the Opening Books

We have implemented an Othello program for the construction and the evaluation of the opening books. The program is a standard program, which incorporates standard techniques including negascout search, iterative deepening, quiescence search, null move pruning, transposition

tables, and so on. The evaluation function is a simple position weight table, trained by the co-evolution learning method used in [8].

We have constructed three opening books by using the combination of different criteria for the expansion policy mentioned in the previous section.:

- **Baseline:** The *Baseline* opening book is essentially a game tree that is constructed by expanding the tree fully in a breath-first manner. It does not take any concept of the trend of the evaluation value into account.
- **Simple Trend:** The *Simple Trend* opening book considers only the *global trend* criteria when deciding whether a node should be expanded, and explores the nodes that are overall increasing. Therefore, it disregards any *local trend* properties, and expands the nodes that are globally increasing.
- **Detailed Trend:** The *Detailed Trend* opening books, take not only the *global trend*, but also the *local trend* into account, by observing the trend of the evaluation value in the last two iterations are increasing or not. Therefore, it expands the nodes that are both globally and locally increasing.

The expanded game trees are directly stored as the opening books. Each node stores essential information such as its evaluation value, game state, and the evaluation of each child node. The evaluation values of the leaf nodes are given by an iterative deepening search, and the depth is within the range of 6 to 12. Each opening book is constructed with a fixed number of 10,000 nodes.

4.2 Analysis of the Constructed Opening Books

The distribution of the nodes at different depths, and the percentage of leaf and interior nodes are given in Table 3. We can observe that by incorporating the concept of *trends* into the expansion policy, it expands the tree to a deeper depth, and reduces its width at the same time.

The *Simple Trend* opening book takes the *global trend* criteria into account, thus it tends to discard the node that does not display global increasing properties, and looks further the node that does. Therefore, the resulting expansion tree is narrower and deeper than that of the *Baseline* opening book.

Since the *Detailed Trend* further considers the *local trend* criteria in the expansion policy, although the maximum depth is the same as that of the *Simple Trend* opening book, the expanded nodes are distributed over deeper depths.

4.3 Performance of the Constructed Opening Books

The performance of the constructed opening books are demonstrated by conducting games between the program that uses the *Baseline* opening book.

The program randomly chooses from best two nodes before the depth of 4. After reaching the depth of 5, the program plays the best move if the current position is an interior node in the opening book. If the current position is a leaf node, the evaluation value will be used as a lower

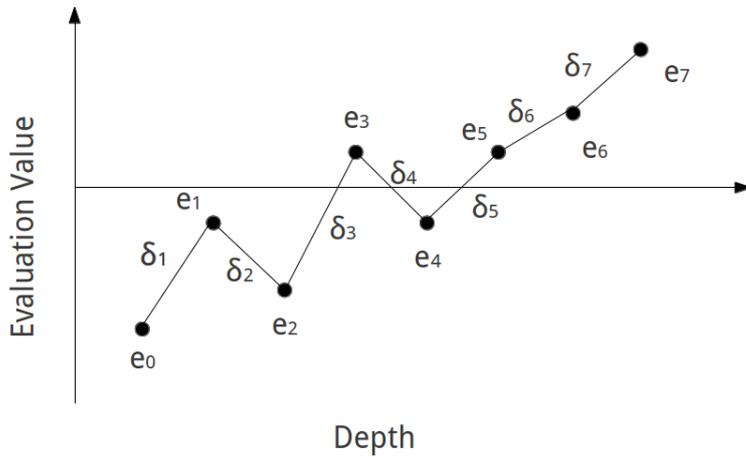


Fig. 2 An example of *accumulation advantage*. The values e_i are the evaluation value of the position when a search is performed to depth i . The value δ_i is the value of the edges between two points, which represents the difference between neighbouring evaluation values. It can be observed that although the initial evaluation value e_0 is low, the overall trend is steadily increasing, which may indicate there is some kind of long-term strategic advantage.

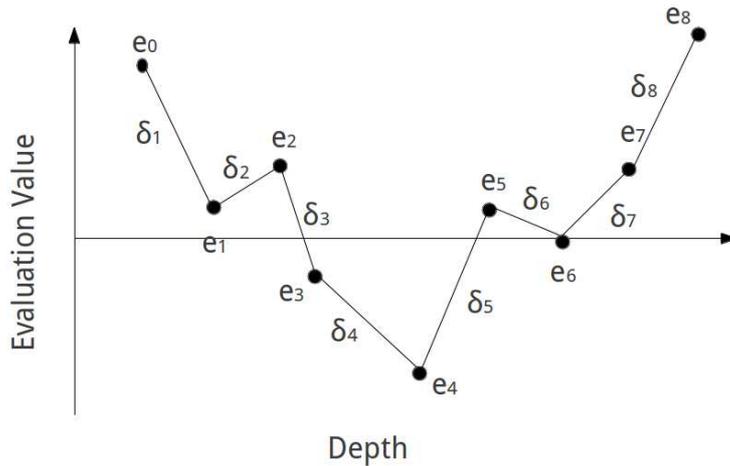


Fig. 3 An example of *existence of long term trap*. The values e_i are the evaluation value of the position when a search is performed to depth i . The value δ_i is the value of the edges between two points, which represents the difference between neighbouring evaluation values. It can be observed that although initially the evaluation value is decreasing, the value starts to increase after the point e_4 , which may indicate there is an existence of a long term trap.

bound to narrow down the window for the search routine.

We have chosen three specific opening positions for the games. The positions are given in Figure 5, Figure 6, and Figure 7. Each position is the resulting position of one initial move from both the Black player and the White player.

For each position, the two opening books will take turns in playing as Black and White. The results are shown in Table 2 and Table 4. The drop out depth of the *Baseline* opening book is 7 for every game, since the *Baseline* is expanded nearly exclusive to the depth of 7, thus it is not specified in the tables.

We can observe in Table 2 that the *Simple Trend* opening

book dominates the *Baseline* opening book in test position 1, and is the roughly the same in test position 2. It is worth noting that the program drops out of the *Simple Trend* opening book earlier when playing as Black in the position 2, and went to win the game, thus demonstrating the property of "the program can handle the position if it drops out of the book", which is what we are aiming for.

Although most lines in the *Detailed Trend* opening book are longer and deeper, the performance against the *Baseline* opening book is not very satisfying. From Table 4 we can observe that although in a lot of the cases, the program stayed in the *Detailed Trend* opening book longer than the

Opening Positions	Black	White	Drop out	Result (Black-White)
Test Position 1	Baseline	Simple Trend	8	White (13 – 51)
	Simple Trend	Baseline	7	Black (36 – 28)
Test Position 2	Baseline	Simple Trend	8	White (25 – 39)
	Simple Trend	Baseline	7	Black (34 – 30)
Test Position 3	Baseline	Simple Trend	4	Black (58 – 6)
	Simple Trend	Baseline	3	White (47 – 17)

Table 2 The performance of the *Simple Trend* opening book versus the *Baseline* opening book. The drop out column shows the depth which the Othello playing program drops out of the *Simple Trend* opening book. The result column shows winner, and the score of the game.

Depth	Baseline	Simple Trend	Detailed Trend
1	4	2	2
2	12	2	2
3	56	7	2
4	244	22	12
5	1396	76	38
6	8200	313	193
7	89	1415	724
8	0	6980	3785
9	0	1184	5243
interior	1723 (17.23%)	2087 (20.87%)	2203 (22.03%)
leaf	8278 (82.77%)	7914 (79.13%)	7798 (77.97%)

Table 3 The analysis of the constructed opening books. The tables shows the number of nodes at each depth, and the number and percentage of interior and leaf nodes.

Baseline opening book, the *Detailed Trend* opening book still lost the game. This is the same for the *Simple Trend* opening book in test position 3.

The most possible reason is that the expansion policy overestimated its long-term advantage, by incorrectly assessing the trend of the evaluation value, since the evaluation function is far from perfect, or there are not enough iterations to correctly assess the sustainability of the increasing trend.

5. Conclusion

In contrast to the other two phases of the game, methods for constructing opening books are less investigated. Since the playing strengths of state-of-the-art programs are really close to each other, more often than not, the results may be decided by the quality of the opening book. Therefore, the importance and demand for good quality opening books are on the rise.

In this research, we proposed a general trend oriented opening book construction method, with the aim of constructing opening books that can capture the strategic nature of the opening phase of a game. From the experimental results, we can see that the “*Simple Trend*” opening book, which is constructed by the proposed method that mainly considers the *global trend* criteria has shown to be promising.

There is still room for improvement in both the expansion policy ϕ and the evaluation method applied for evalu-

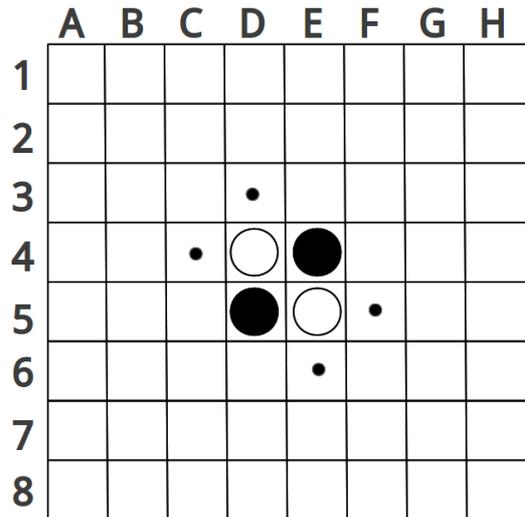


Fig. 4 The starting position of Othello. Black is the first player to move, and possible initial moves are C4, D3, E6, and F4, which are marked with a dot.

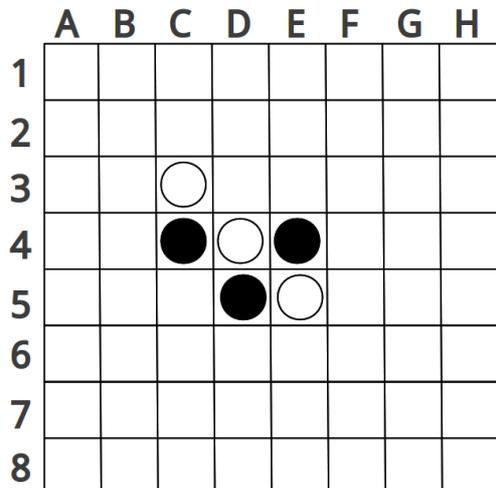


Fig. 5 Test Position 1. The position results from the opening moves C4 and D3. Black to move.

Opening Positions	Black	White	Drop out	Result (Black-White)
Test Position 1	Baseline	Detailed Trend	6	Black (43 – 21)
	Detailed Trend	Baseline	9	Black (38 – 26)
Test Position 2	Baseline	Detailed Trend	8	Black (57 – 7)
	Detailed Trend	Baseline	7	Black (54 – 10)
Test Position 3	Baseline	Detailed Trend	4	White (55 – 9)
	Detailed Trend	Baseline	3	Black (50 – 14)

Table 4 The performance of the *Detailed Trend* opening book versus the *Baseline* opening book. The drop out column shows the depth which the Othello playing program drops out of the *Detailed Trend* opening book. The result column shows winner, and the score of the game.

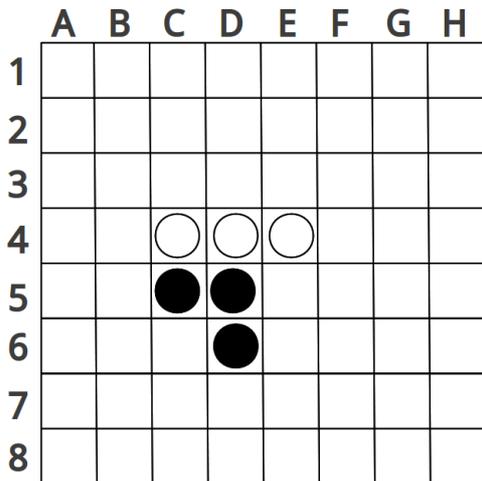


Fig. 6 Test Position 2. The position results from the opening moves E6 and F4. Black to move.

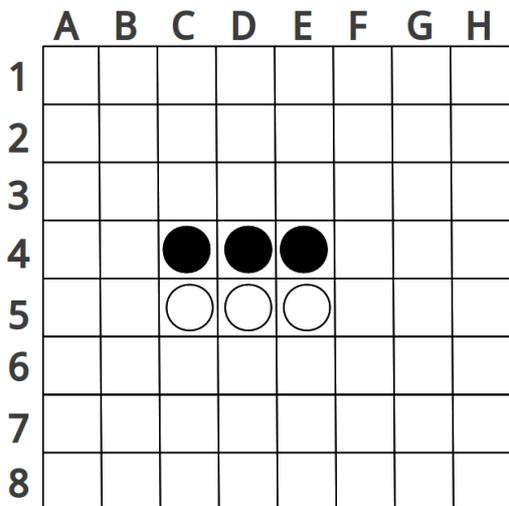


Fig. 7 Test Position 3. The position results from the opening moves C4 and C5. Black to move.

ating candidate nodes. Developing methods for more accurate estimation of the sustainability of a trend will certainly be a prime priority.

Other enhancements, such as taking the opponent model into consideration, and applying the proposed method to other games, such as Chess, Go, and Shogi, are also very interesting and promising directions for future research.

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