A Study of Effective Rule-Based Othello Strategies

Focusing on the Minimax Approach and the Game Phase-Dependent Hybrid Approach

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Introduction

Othello is a strategic board game characterized by its simplicity in rules yet complexity in strategy. The author hypothesizes that traditional heuristic-based strategies — such as Random, Greedy, Corner, and Positional — are inherently limited in their ability to adapt to the dynamic nature of the game, since the advantageous move configurations in Othello constantly shift depending on the opponent's actions. To overcome these limitations, we propose and evaluate two rule-based strategic frameworks: **(1) Minimax with Alpha-Beta Pruning** and **(2) Hybrid Through Time**, which dynamically switches evaluation criteria based on the current phase of the game. Minimax with Alpha-Beta pruning, systematically explores future game states while significantly reducing computational overhead by pruning irrelevant branches. Hybrid Through Time addresses a recognized limitation of fixed-strategy methods, hypothesizing that different strategic considerations — such as mobility, positional(corner and edge) advantage, and Minimax-based search — should be selected at different game stages. We quantitatively assess the performance of our proposed methods through rigorous tournament evaluation against aforementioned traditional strategies.

Strategy 1: Minimax with Alpha-Beta Pruning

This strategy combines the Minimax algorithm with Alpha-Beta pruning to efficiently search the game tree and determine optimal moves in Othello. The motivation behind adopting this approach is to systematically explore possible future moves while controlling the exponential complexity inherent to exhaustive search. Minimax recursively simulates two opposing players, one maximizing their own advantage, and the other minimizing it. Since full tree exploration is computationally intensive, we impose a depth limit k for practical efficiency. Alpha-Beta pruning enhances Minimax by eliminating the need to evaluate branches that cannot affect the final decision, significantly reducing computational cost.

Definition 1: Minimax Algorithm

The Minimax algorithm recursively evaluates the game tree, alternating between maximizing and minimizing states. At each step, it selects the optimal move by assuming optimal play from both sides:

$$\text{Minimax}(s) = \begin{cases} Eval(s), & \text{if terminal state or depth=k} \\ \max_{a \in Actions(s)} \text{Minimax}(Result(s,a)), & \text{if } s \text{ is a maximizing state} \\ \min_{a \in Actions(s)} \text{Minimax}(Result(s,a)), & \text{if } s \text{ is a minimizing state} \end{cases}$$

In our implementation, we set $k = 4$. Below is a description of Alpha-Beta pruning:

Definition 2: Alpha-Beta Pruning

Alpha-Beta pruning significantly reduces the number of nodes evaluated in the search tree by pruning branches that cannot possibly influence the final decision Knuth and Moore (1975). It utilizes two parameters:

- Alpha (α): The best (maximum) score found so far along the path for the maximizing player.
- Beta (β): The best (minimum) score found so far along the path for the minimizing player.

Pruning occurs when:

$$\text{value} \leq \alpha \quad \text{or} \quad \text{value} \geq \beta$$

Using Definitions 1 and 2, we evaluate the appropriateness of our strategic decisions in each state using the evaluation function described below.

Definition 3: Evaluation Function

The evaluation function calculates board scores using positionWeights:

$$\text{score} = \sum_{i,j} positionWeights_{i,j} \times ownership_{i,j}$$

where

$$ownership_{i,j} = \begin{cases} +1, & \text{if position } (i,j) \text{ is occupied by the player} \\ -1, & \text{if position } (i,j) \text{ is occupied by the opponent} \\ 0, & \text{otherwise (empty)} \end{cases}$$

The `positionWeights` matrix is designed based on our heuristic and defined as follows:

$$positionWeights = \begin{bmatrix} 100 & -20 & 10 & 5 & 5 & 10 & -20 & 100 \\ -20 & -50 & -2 & -2 & -2 & -2 & -50 & -20 \\ 10 & -2 & 5 & 1 & 1 & 5 & -2 & 10 \\ 5 & -2 & 1 & 0 & 0 & 1 & -2 & 5 \\ 5 & -2 & 1 & 0 & 0 & 1 & -2 & 5 \\ 10 & -2 & 5 & 1 & 1 & 5 & -2 & 10 \\ -20 & -50 & -2 & -2 & -2 & -2 & -50 & -20 \\ 100 & -20 & 10 & 5 & 5 & 10 & -20 & 100 \end{bmatrix}$$

Strategy 2: Hybrid Through Time

This strategy dynamically selects strategic approaches based on the number of disks placed on the board. The motivation behind this approach arises from the hypothesis that using a single strategy throughout the entire game can be suboptimal, as each phase of an Othello game (early, mid, end-game) typically requires different strategic priorities and methods. The following defines how different strategies are applied across game phases by leveraging the parameters k and l.

Definition 4: Hybrid Through Time

Given the number of placed stones n on the board:

$$\text{Strategy}(n) = \begin{cases} \text{Opponent Mobility Reduction}, & \text{if } n < k \\ \text{Corner Strategy}, & \text{if } k \leq n < l \\ \text{Minimax with Alpha-Beta Pruning}, & \text{if } n \geq l \end{cases}$$

In our practical heuristic, optimal performance was achieved with the parameters $k = 15$ and $l = 40$. Each sub-strategy is evaluated as follows:

- **Opponent Mobility Reduction:** Select moves minimizing opponent's mobility (number of valid moves).
- **Corner Strategy:** Select moves maximizing the positional weight score (`positionWeights`).
- **Minimax with Alpha-beta Pruning:** Use Minimax algorithm with Alpha-Beta pruning as defined in `Strategy 1`.

Experiment and Discussion

Our proposed strategies were evaluated through tournament simulations using the Othello AI Arena. The experiments were conducted during a total of 30 tournament matches between six strategies (Strategy 1, Strategy 2, and four traditional strategies - Random, Greedy, Corner Strategy, and Positional Strategy). The primary performance metric was the number of matches won by each strategy.

Table 1: Tournament results between six strategies (total 30 games)

Strategy	Win Rate (%)	Wins	Losses	Draws	Games
Hybrid	90.0	9	1	0	10
Minimax_abpruning	60.0	6	4	0	10
Corner Strategy	55.0	5	4	1	10
Random	50.0	4	4	2	10
Positional Strategy	25.0	2	7	1	10
Greedy	20.0	2	8	0	10

The empirical results indicate that the proposed Hybrid Through Time approach substantially outperforms both the conventional baseline strategies and the standalone Minimax with Alpha-Beta pruning. Specifically, Hybrid Through Time achieved a 90% win rate, empirically supporting the hypothesis that dynamically adjusting strategic focus according to game phases effectively addresses Othello's changing strategic demands. The Minimax strategy demonstrated moderate success, surpassing most baseline heuristics, affirming that systematic, search-based methods reliably produce competent performance.

Despite the promising performance of our proposed strategies, several limitations must be acknowledged. First, while the Minimax algorithm combined with position-based evaluation provides systematic foresight of possible opponent moves, the optimality of the predefined positionWeights matrix remains uncertain. The current weights were empirically chosen without rigorous validation against alternative weighting schemes, potentially limiting strategic effectiveness. Second, although the Hybrid Through Time strategy improves strategic flexibility by dynamically adjusting its approach according to game phases, it is unclear whether the current sub-strategies assigned to each phase represent the most effective combination. The performance observed might thus be further improved through alternative strategic assignments or by refining the criteria for transitioning between game phases.

To address the aforementioned limitations and enhance the robustness and adaptability of our Othello agents, several future research directions are suggested. A critical next step involves rigorously optimizing and validating the positional weighting matrix through systematic parameter tuning methods or evolutionary algorithms. This approach may identify superior weight configurations that enhance strategic effectiveness beyond current heuristics. Furthermore, exploring alternative sub-strategies and systematically evaluating their suitability for different game phases could yield improvements in the Hybrid strategy's flexibility and overall effectiveness. Integrating adaptive mechanisms, such as reinforcement learning or self-play optimization, could dynamically identify and assign the most suitable sub-strategies for given game states, thus further optimizing the agent's adaptability. These refinements are anticipated to improve strategic performance significantly, ensuring our agents maintain competitive advantages across diverse gameplay scenarios.

Code available at: `https://github.com/LimDoHyeon/Othello-agent`

References

Knuth, D. E. and Moore, D. W. (1975). *An Analysis of Alpha-Beta Pruning.* North-Holland Publishing Company.