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A potential model pruning in Monte-Carlo *go*

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Abstract: In this study, we tackled the reduction of computational complexity by pruning the *igo* game tree using the potential model based on the knowledge expression of *igo*. The potential model considers *go* stones as potentials. Specific potential distributions on the *go* board result from each arrangement of the stones on the *go* board. Pruning using the potential model categorizes the legal moves into effective and ineffective moves in accordance with the threshold of the potential. In this experiment, 5 kinds of pruning strategies were evaluated. The best pruning strategy resulted in an 18% reduction of the computational complexity, and the proper combination of two pruning methods resulted in a 23% reduction of the computational complexity. In this research we have successfully demonstrated pruning using the potential model for reducing computational complexity of the *go* game.

Keywords: Monte-Carlo *go*, Potential, Pruning, Range search

1 INTRODUCTION

Monte-Carlo *go* [1] is the computer *igo* which satisfy the strength without the knowledge expressions of *igo*. Monte-Carlo *go* is very computationally intensive. However, reduction of the computational complexity is possible by properly pruning the *igo* game tree. In this study, we tackled the reduction of computational complexity by the pruning the *igo* game tree using the potential model.

2 PROPOSED METHOD

The proposed method in this research is consists of Monte-Carlo *go* and potential model.

2.1 Monte-Carlo *go*

Monte-Carlo *go* evaluates legal moves at each phase to choose the next move by simulation based on the Monte-Carlo search. Monte-Carlo search consists of many moves of a simulation. This simulation is called "Play Out." Play Out involves both sides constantly choosing the next move alternately and randomly from the current phase to the end game. Play Out calculates an estimation ($\overline{X_i}$) for each legal move (i). (s_i) is the number of times of Play Out. (X_i) is the total considerations of Play Out. In Play Out, if the offensive wins, the consideration is 1, and if it loses, the consideration is 0. As a result, the move which has the best estimation is selected as next move.

$$\overline{X_i} = \frac{X_i}{s_i} \qquad (1)$$

2.2 Potential model

Stones influence the possibility of the surrounding intersection becoming their territory. The potential model is to quantify these influences by assuming *go* stones as potentials following earlier studies [2-4].

2.2.1 Definition of potential

The definition of potential in this experiment is shown in Formula (2-4) and Table 1. The plus and minus of Formula (3) is switched by the setting of proposed method. A potential gradient are calculated by Geographical Information Systems [5].

$$r = \sqrt{(X - x_i)^2 + (Y - y_i)^2} \qquad (2)$$

$$P_i = \pm \frac{1}{2^r} \qquad (3)$$

$$P_{all} = \sum_{\mathrm{k}=1}^{\mathrm{n}} P_i(X, Y) \qquad (4)$$

Table 1. Mathematical expression

r	Euclidean distance
x_i, y_i	Intersection of $Stone_i$
$P_k(X, Y)$	Potential to intersection (X, Y) from $Stone_k$
n	Total number of stone on the *go* board
$P_{all}(X, Y)$	Total potential to
$PG(X, Y)$	A potential gradient at an intersection.

2.2.2 Pruning using potential model

Potential Filters

Potential Filters are pruning instruments in this experiment. At each phase to choose the next move, these Filters pruned legal moves according to the following procedures:

i. Calculate potential distribution result from arrangement of go stones on the *go* board.
ii. Rank legal moves by each magnitude of potential (or potential gradient.)
iii. Categorize the ranked legal moves into effective and ineffective moves in accordance with thresholds for the ranking. (Each Potential Filter has unique threshold levels.)
iv. Eliminate the ineffective moves from candidates for the next move. (Run Monte-Carlo search only on effective moves.)

In accordance with the number of eliminated legal moves, the computation load of Monte-Carlo search is reduced. Said differently, the Potential Filters reduce the range of search spaces on the *go* board.

Configurations of Potential Filters

Table 2 shows the threshold conditions of the 5 kinds of Filters. Each Potential Filter ranked legal moves in descending order of potential or potential gradient values, and categorized in accordance with each threshold condition for the ranking. All Filters mutually reduced by half the number of legal moves. Thus all Filters reduced by half the computational load at each phase to choose the next move.

On and Off Switch of Potential Filter

Potential Filters had a switching point, which switched their states ON and OFF. This switching point was within a range of legal intersection numbers on the *go* board. A switching point was selectable from 2 to 81 when the board size was 9 x 9 (= 81), or from 2 to 169 when the board size was 13 x 13 (= 169).

During the course of a game, in the case a remaining legal move number on the *go* board was above a switching point, the Potential Filters were ON. If a remaining legal move number was under a switching point, the Potential Filters were OFF. In this experiment, boundaries where Potential Filters became ineffective from effective were measured by changing the switching point. The boundaries were the points where winning percentages crossed an average winning percentage between two normal Monte-Carlo *go*.

Monte-Carlo search has higher performance when a game tree is small. In contrast, Monte-Carlo search has low performance when a game tree is large. Thus, pruning is effective in the opening game. However, afterwards, pruning gradually becomes ineffective.

3 STRENGTH OF MONTE-CARLO *GO* WITH POTENTIAL FILTERS

The strength of Monte-Carlo *go* with Potential Filters was indicated by its winning percentage against normal Monte-Carlo *go*. Monte-Carlo *go* with Potential Filters used the initiative move while normal Monte-Carlo *go* used the passive move. In a match-up between two normal Monte-Carlo *go*, the winning percentage of the initiative move was 57% when board size was 9 x 9, or 51% when board size was 13 x 13. (The winning percentage of initiative exceeded 50% because the initiative move was advantageous.) Therefore, 57% or 51% is considered the average level of normal strength.

4 RESULTS AND OBSERVATION

The strength of Monte-Carlo *go* with Potential Filters is shown in Fig. 1, upper (board size: 9 x 9) and lower (board size: 13 x 13) graphs, left axis. Strength transitioned with Filters and switching points. A winning percentage of 57% or 51% and calculating the results of the Random Filter were important for comparing and evaluating the effects and tendency of Potential Filters. Total Play Out numbers needed in one game are shown in Fig. 1, upper and lower graphs, right scale. Total Play Out numbers transitioned with these Filters and switching points.

In theory, when the Random Filter was used, the next move became the best move by Monte-Carlo search 50% of the time and the second or several moves thereafter by Monte-Carlo search the other 50% of the time.

In the case that the number of legal moves was large, Monte-Carlo search had low precision. Thus, there was no big decrease of strength, because there was no defining difference between the best move and the second or several moves thereafter by Monte-Carlo search. The precision of Monte-Carlo search increased with a decrease in the number of legal moves. The strength of the Random Filter decreased gradually with a decrease in the number of legal moves.

Potential Filter 1 became the bias around which black stones gathered. In the opening game, these collective black stones effectively strengthened initiative territory. However, in the middle game, the initiative move could not expand its territory. As a result, the passive move acquired more territory than the initiative move on the *go* board. When strength exceeded average (57% or 51%), Potential Filter 1 properly pruned ineffective moves that Monte-Carlo search was unable to do. Thereafter, the strength of the Potential Filter 1 decreased gradually with a decrease in the number of legal moves and an increase in the precision of Monte-Carlo search. In fact, the pruning of Potential Filter 1had encumbered the precision of Monte-Carlo search.

Potential Filter 2 became the bias where black stones were attracted around white stones. In the opening game, black stones effectively suppressed white stones. However, in the middle game, black stones were removed easily by collective white stones. As a result, the passive move acquired more territory than the initiative move on the *go* board. When strength exceeded average (57% or 51%), Potential Filter 2 properly pruned ineffective moves.

Potential Filter 3 became the bias where black stones were scattered on the *go* board. These black stones were removed easily by collective white stones. As a result, the passive move acquired more territory than the initiative move on the *go* board. In the opening game, Potential Filter 3 barely pruned ineffective moves. However, Potential Filter 3 decreased the strength in comparison with other Filters more gently.

Potential Filter 4 became the bias where black stones were attracted around black and white stones, and areas between black and white stones were closed. This is important in *igo*. Potential Filter 4 could prune more properly than the other Filters, but decreased the strength in comparison with other Filters more drastically in the middle game.

Potential Filter 5 became the bias where stones were attracted around black and white stones. Potential Filter 5 could prune more properly than the other Filters, but decreased the strength in comparison with other Filters more drastically in the middle game as well as Potential Filter 5.

As for Combination, Potential Filter 5 and Potential Filter 3 combined pruned a game tree more properly than Potential Filter 5 alone. In the opening game, Potential Filter 5 was effective and this initiative had high strength. However, in the middle game, Potential Filter 5 decreased the strength in comparison with other Filters more drastically. On the other hand Potential Filter 3 decreased the strength in comparison with other Filters more gently. So the strength keeps the average for a longer time by switching Potential Filter 5 to Potential Filter 3 at the point where the strength of Potential Filter 5 began to decline (switching point 68 or 145).

4 CONCLUSION

In this study, we tackled the reduction of computational complexity by pruning the *igo* game tree using the potential model based on the knowledge expression of *igo*. In our experiments, 5 kinds of pruning strategies (Potential Filters) were evaluated for their removal effect. Maintaining normal strength of Monte-Carlo *go*, Potential Filter 4 or 5, based on potential gradient distribution or homopolarity potential distribution, could reduce up to 18% of total Play Out numbers needed in one game. Potential gradient and homopolarity potential could identify important areas around black and white stones as well as close areas between black and white stones. In addition, combining Potential Filter 5 and Potential Filter 3 could reduce up to 23% of total Play Out numbers by switching Potential Filter 5 to Potential Filter 3 at the point where the strength of Potential Filter 5 began to decline (switching point 68 or 145). This shows the tendency of *igo* transition as the game progresses.

In this research we successfully demonstrated pruning using the potential model for reducing computational complexity of the *go* game. However, our experiments were limited as the Play Out number was set at 100 and the board size was set at 9 x 9 or 13 x 13. For our future research, we intend to expand the proposed strategy to tackle more complex games with larger Play Out numbers and *go* board size.

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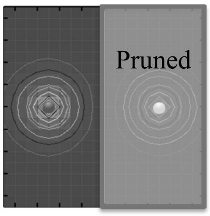
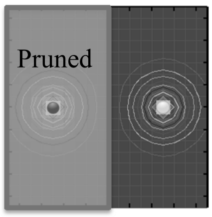
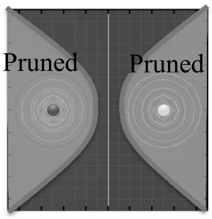
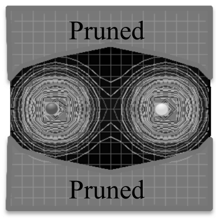
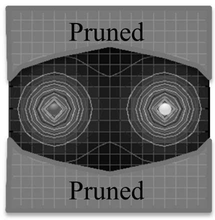
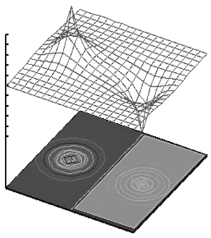
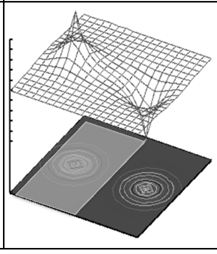
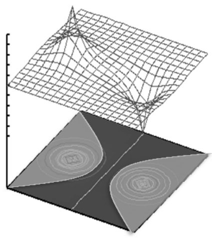
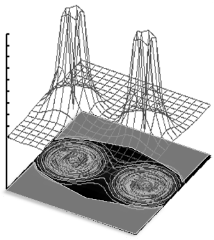
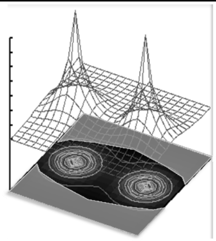
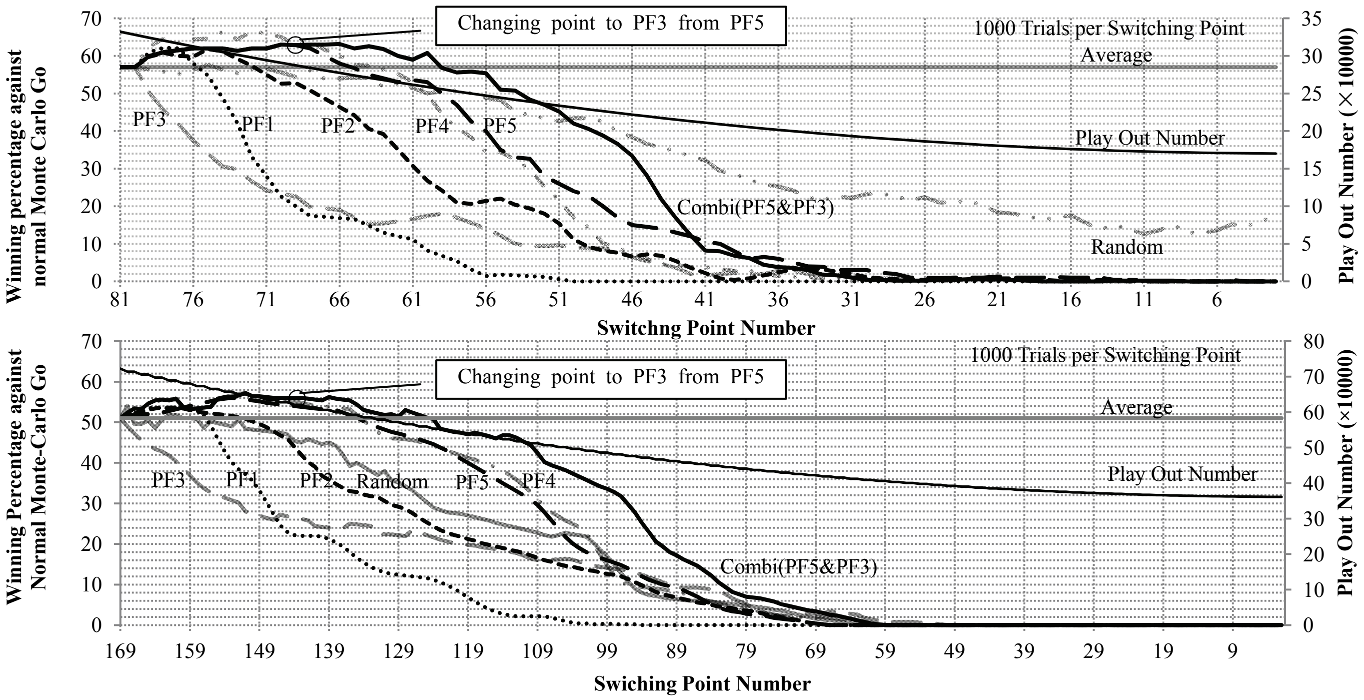
Table 2. Types of Potential Filters

Method	1	2	3	4	5
Ranking	Potential	Potential	Potential	Gradient	Potential
Black/White	+/−	+/−	+/−	+/−	+/+
Filtering	Low 50%	Top 50%	Above 25% and below 75%	Low 50%	Low 50%
Overhead					
Landscape					



	9 x 9			13 x 13		
	Border	Play Out Number	Reduction Rate	Border	Play Out Number	Reduction Rate
Random	–	332000	00.0	–	722400	00.0
Potential Filter 1	77	316300	04.7	157	673200	06.8
Potential Filter 2	73	301400	09.2	152	649950	10.2
Potential Filter 3	–	332000	00.0	–	722400	00.0
Potential Filter 4	64	270800	18.4	135	592350	18.0
Potential Filter 5	64	270800	18.4	135	592350	18.0
Combination	59	255500	23.0	125	559600	22.5

Fig. 1. Strengths of Monte-Carlo *go* with Potential Filters