(D,d)OM-Search For Practical Use

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Abstract

As a kind of the speculative play, we proposed OM-Search and its generalization, called (D,d)OM-Search, where D stands for the depth of search by the player and d for the opponent's depth of search. However, it has some disadvantages to apply for game tree search in practical so that we propose a new type of (D,d)OM-Search in order to supplement their weak points. And we have performed some experiments to prove the validity of using it in Shogi. Consequently, the performance of new type (D,d)OM-Search is slightly better in comparison with pure (D,d)OM-Search.

Keywords: Speculative play, (D,d)OM-Search, (D,d)*OM-Search, Quality of evaluation function, Shogi;

1 Introduction

In the previous study, the validity of (D,d)OM-Search has been indicated in Othello [2]. On the other hand, some unexpected results were obtained which could be recognized as an undesirable effect of the poor evaluation function. In the latest study, the risk of using OM-Search is pointed out by Donker et al [4] [5]. According to their opinion, the risk appeared because of poor evaluation function and imperfect knowledge on the opponent. A point of agreement should be recognized as a significant part of the results. Therefore, we propose a new type of (D,d)OM-Search as one of the approach to solve these problems. Firstly, we outline the definition of (D,d)OM-Search and point out the weak points in terms of difference between game tree model and real game tree search. Afterward, we propose a new type of (D,d)OM-Search that is called (D,d)*OM-Search. Then, we perform some experiments in order to investigate the performance of (D,d)*OM-Search in the domain of Shogi. Not only performance of (D,d)*OM-Search but also the influence of the quality of evaluation function on OM-Search could be focused on these experiments.

2 (D,d)OM-Search

2.1 Definition

The definition of (D,d)OM-Search is shown as follow.

Definition 1 ((D,d)OM-Search) *is a kind of the search strategy by which a player try to obtain better result than that by Min-Max strategy. The search depth of max player is defined* ***D****, the search depth of min player is defined* ***d****, in addition* ***D*** *is always bigger than* ***d****. Each player use same static evaluation function EV_f.*

Definition 2 $V_{om}^{(D,d)}(P)$ *represents the value at position P by (D,d)OM-Search and $V_{mm}^{d}(P)$ that by Min-Max strategy with serach depth d.*

Then the algorithm of (D,d)OM-Search can be defined by the following formulations.

$$V_{om}^{(D,d)}(P) = \begin{cases} \max\limits_i V_{om}^{(D,d)}(P_i) & \text{if P is a max node} \\ V_{om}^{(D,d)}(P_j) \text{ with j} & \\ \text{ such that } V_{mm}^{m}(P_j) = \min\limits_i V_{mm}^{m}(P_i) & \text{if P is a min node} \\ & \text{at } u^{th} \text{ ply}(1 \leq u \leq m) \\ \min\limits_i V_{om}^{(D,d)}(P_i) & \text{if P is a min node} \\ & \text{at } v^{th} \text{ ply}(m+1 \leq v) \\ EV_f(P) & \text{if P is a node at } D^{th} \text{ ply} \\ & \text{ or a terminal node} \end{cases} \tag{1}$$

$$V_{mm}^{d}(P) = \begin{cases} \max\limits_i V_{mm}^{m}(P_i) & \text{if P is a max node at } u^{th} \text{ ply} \\ \min\limits_i V_{mm}^{m}(P_i) & \text{if P is a min node at } u^{th} \text{ ply} \\ EV_f(P) & \text{if P is a node at } (d+1)^{th} \text{ ply} \\ & \text{ or a terminal node} \end{cases} \tag{2}$$

2.2 Risk

The example is shown in Figure.1, now we assume the depth of max player is 5, the depth of min player is 3 respectively. Lv1 denotes the first opportunity in order to choice the move among all legal moves for min player; Lv2 denotes the second opportunity to select the move. There are any problem has been not occurred in the game tree model. Because the evaluation value was never changed wherever root position was set up. However, if (D,d)OM-Search was performed in real game tree search, it no longer has enough reliability in order to predict opponent move when max player use (D,d)OM-Search in Lv2 although such a harmful influence was never appeared in Lv1. In this case, if max player try to predict the move of min player perfectly, the depth of max player should be more than 6. Because to predict the move of min player whose depth is 3 in Lv2 corresponds to the search with 3 plus opponent 's depth in root position. To predict the move of opponent in Lv1 equals to the search with 1 plus opponent 's depth in root position incidentally.

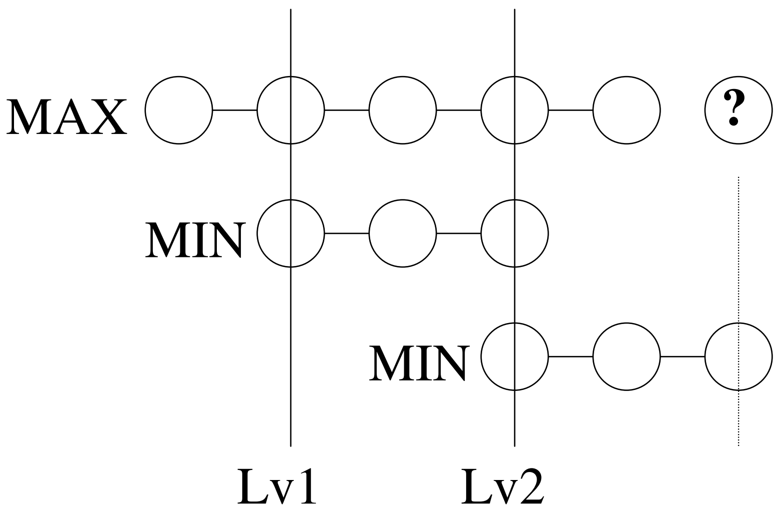

Figure 1: The risk of (D,d)OM-Search

3 (D,d)*OM-Search

Then the algorithm of (D,d)*OM-Search can be defined by the following formulations.

$$V_{om}^{(D,d)}(P) = \begin{cases} \max\limits_i V_{om}^{(D,d)}(P_i) & \text{if P is a max node} \\ V_{om}^{(D,d)}(P_j) \text{ with j} & \\ \text{ such that } V_{mm}^{m}(P_j) = \min\limits_i V_{mm}^{m}(P_i) & \text{if P is a min node} \\ & \text{at 1st ply} \\ \min\limits_i V_{om}^{(D,d)}(P_i) & \text{if P is a min node} \\ & \text{at } v^{th} \text{ ply} (2 \leq v) \\ EV_f(P) & \text{if P is a node at } D^{th} \text{ ply} \\ & \text{ or a terminal node} \end{cases} \quad (3)$$

$$V_{mm}^{d}(P) = \begin{cases} \max\limits_i V_{mm}^{m}(P_i) & \text{if P is a max node at } u^{th} \text{ ply} \\ \min\limits_i V_{mm}^{m}(P_i) & \text{if P is a min node at } u^{th} \text{ ply} \\ EV_f(P) & \text{if P is a node at } (d+1)^{th} \text{ ply} \\ & \text{ or a terminal node} \end{cases} \quad (4)$$

4 Experimental Design

We prepared two types of positions from the record of professional player and the publication of Shogi problem [7] for experimental testbeds. The 40 unbalanced positions have been prepared in 20 plies before resignation and the other 40 balanced position in 20 plies after initial position. The self-play experiments have been performed between four types of player as follows and normal min-max player P3 whose search depth is 3.

- P5 notes the Min-Max player with search depth = 5.
- OM5 notes the pure (D,d)OM-Search player with search depth = 5.
- OM5*a notes the (D,d)*OM-Search player with search depth = 5, but it has complicated static evaluation function.
- OM5*b notes the (D,d)*OM-Search player with search depth = 5, but it has simple static evaluation function.(only material)

OM5*a and OM5*b have prepared to investigate the relationship between OM-Search and the quality of evaluation function. We selected the Shogi program TACOS, that is developed by our laboratory, for the experiment.

5 Experimental Result

The experimental result has shown in Table 1, 2.

player	score
P5	31-9
OM5	18-22
OM5*A	21-19
OM5*B	24-16

Table 1: The result of the match against P3 in disadvantageous positions of max player

The experimental result showed us the serious problem, i.e. the player has large advantage without (D,d)*OM-Search in comparison with the player using (D,d)*OM-Search. Furthermore, the

player	score
P5	36-4
OM5	19-21
OM5*A	26-14
OM5*B	15-14(11)

Table 2: The result of the match against P3 in balanced positions

Notice: the number besides () represents the number of draws.

winning ratio of the player who uses simple static evaluation function is higher than the player of using complicated static evaluation function in unbalanced positions. Consequently, we would never conclude that (D,d)*OM-Search could be overcame the weak point of OM-Search although the performance of (D,d)*OM-Search is slightly better in comparison with pure (D,d)OM-Search.

6 Concluding Remarks

Unfortunately, our new approach was failed in this experiment although we could observe the effective of (D,d)*OM-Search in comparison with pure (D,d)OM-Search. We recognized that the factors of unexpected experimental result are the horizon effect, the imperfect evaluation function and the timing of using (D,d)*OM-Search that has been mentioned in [6]. It is one of the greatest challenges to erase the horizon effect or to obtain the perfect evaluation function in complicated game like a Shogi. However we should be focused on the timing of using speculative play like a (D,d)*OM-Search because other approaches are quite difficult practically. In addition, it is also significant to investigate the speculative play that makes the opponent confusional as our future works.

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