A Classification of the Phases in Shogi Game using Self-Organizing Maps

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Abstract– Computer Shogi programs are still in development to defeat the professional players. One of the main problems exists in estimating the status of the game phases. It is said that there are three phases in the Shogi game, so called, opening, middle and endgame phase. The appropriate strategy to be selected differs depending on the proceeding game phase. In the present paper, we have carried out the classification of the phases using Self-Organizing Maps. The results show the promising feature.

1 Introduction

Chess playing systems, developed recently, are on a level of human professionals. These achievements depends on the development of the computers, especially in terms of calculation speed, because almost all of these systems are based on the techniques of searching a huge space[1]. Not only these developments on the computer hardware but also those of software play a great role. In the games like Chess, it is important to estimate correctly some more steps further.

After "Deep Blue"[2] specially designed to play Chess by IBM defeated the Champion, the research interest has switched to Go and Shogi in which search space is much larger than Chess. As for Go, the search space is larger than Shogi because the board is wider. The research of Go is active worldwide, but it is much more difficult problem at present, because the strategy is quite different from those of Chess or Shogi. Shogi playing system is researched actively in Japan. On the other hand, the strategy in Shogi can be easily compared with Chess. This is one of the reason why we chose Shogi as a target problems. Because the pieces taken from opponent can be used as players' side, the search space of Shogi is much larger than that of Chess. Especially, Tsume-Shogi, which means a kind of chess in the sequential checkmating at endgame phase are quite well researched[3], where the computer program can find the optimal solution by exhaustive search. It is a kind of trade-offs between the remaining the time to play and the searching speed.

It is important to know at which phase players are playing. In other words, to establish the appropriate evaluation function for the game phase is one of the main problems. However, a systematic setting method of the evaluation function is not established yet. The development for what depends on system creator's knowledge strongly. Recently, it has been tried to obtain the evaluation function through machine learning in relatively simple games. The backgammon by Tesauro is famous[4] called TD-Gammon. TD-Gammon learned evaluation function from the results from self-plays using the neural network and the Temporal Difference Learning (TD Learning). As a result, it learned to play the world class backgammon. Neural Networks or TD Learning have been applied in other games to obtain good strategy, but in chess[5], Go[6] and Shogi[7][8][9], the results have been far from the champion level.

The application of the TD Learning to Shogi was tried by Don Beal first[7]. In [7], it focused only to the numbers of pieces and learned the pieces' importance. The obtained importance reflect well that of popular computer Shogi programs. The learning of the evaluation function by TD learning has been studied[9]. In [9], it took a lot of time to learn because this used a result of one whole game as a teaching data. In this system, they use a single evaluation function to be learned through the game, and it is hand to achieve a good result.

It is said that evaluation functions are different in Shogi depending on its phases, i.e., of the game, two or more evaluation functions are used properly[10][11][12]. This means that the evaluation function should be selected on

changed depending on the proceeding of the game. It is required to classify the phases of the game appropriately.

The classification of the phases of the game is tried in this paper. We had been engaged in the development of the classification method by quantifying a subjective uncertainty[13]. However, the result was 50% of accurate compared with the classification of the player. In this paper, we have paid attention to Self-Organizing Maps (SOM) in order to classify the phases. SOM is known as the classification of the multidimensional data into 2 dimensions in an effective way, and used popularly as an analysis tool. The phases of the game were classified by SOM, the feasibility of the proposed method are examined using the record of the professional Shogi Players. The methods to measure at which stages the player now is have been investigated by T. Kato et al.[14] or A. Kawata [15], in which the number of moves is the key. In this proposed method, the classification depends on the content of the square rather than the number of moves.

2 Phases in Shogi game

Like Chess, Shogi is deterministic, perfect information, zero-sum game of strategy between two players. The object of the game is to capture the opponent's King. Shogi is played on a nine-by-nine board. The vertical columns are called files, the horizontal rows are called ranks or rows. Each player has twenty pieces: one King are indicated, two Gold Generals, two Silver Generals, two knights, two Lances, one Rook, one Bishop and nine Pawns (Figure 1 and Table 1). The player moving up the board and making the first move is referred as black and his opponent are indicated white in the records, although in real Shogi sets all pieces have the same color. Top three ranks on board are called White's Zones and bottom of them are called Black's Zones. Other ranks are called Central Zones. Black's Zones is promotion zones for White and White's Zones is promotion zones for Black.

There are three phases in the Shogi game, opening, middle and endgame phase, although each phase is not strictly defined, it would be characterized as below.

- OpeningFFrom the beginning to start of the fight,
- MiddleFFrom start of the fight to start of the bringing the king near checkmate,
- EndgameFFrom bringing the king near checkmate to last.

All the heuristic rules are implemented in the Shogi playing game by hand. The different strategy is made in each Shogi phase, that is,

- OpeningFPreparation of the fight is important.
- MiddleFMaterial is important.
- EndgameFSpeed is more important than material.

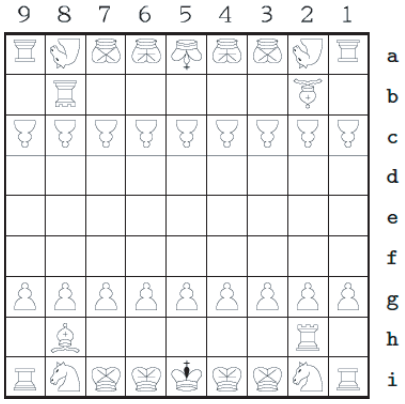

Figure 1: First state on board in Shogi

Table 1: Each piece in Symbol

Symbol	English
	Pawn
	Lance
	Knight
	Silver General
	Gold General
	Bishop
	Rook
	King

The function that evaluates position dependency changes in each phase, too. Kato's et al. and Kawata's et al. methods tried to quantify a game phase by steps which denote how far a game has proceeded from the beginning. They use neural network in their approach. The value $\frac{0.8}{[end\ number\ of\ move]} \times [number\ of\ moves] + 0.1$ are used as teaching signals there. It showed be pointed out that the error grows in this method in middle phases and endgame. In other words, this approach seems to be effective only in the Opening phase. In this approach, they assume the degree of progress is linear. There is a great variety of the length of phases in each game. One may have long middle and short endgame and others may have short middle and long endgame, etc. We cannot distinguish the phase using only the proceeding steps.

3 Classification of the phases by SOM

3.1 Self-Organizing Maps

SOM proposed by T. Kohonen [16] can classify the multidimensional data without preliminary knowledge. SOM is composed of two layers, that is, the input layer and the output layer. The units in the input layer connect with all units in the output layer.

When input data $\boldsymbol{x} = (x_1, \cdots x_n)$ of is given to the input layer, unit $\boldsymbol{m}_c$ $i \neq$ the distance is the shortest to the data is found among units $\boldsymbol{m}_i = (m_{i1}, \cdots, m_{in})$ in the output layer. Let us denote the distance from $\boldsymbol{x}$ to $\boldsymbol{m}_i$ by

$|\boldsymbol{x} - \boldsymbol{m}_i|$, then;

$$|\boldsymbol{x} - \boldsymbol{m}_c| \quad = \quad \min_i |\boldsymbol{x} - \boldsymbol{m}_i|. \qquad (1)$$

where $\boldsymbol{m}_c$ is called a bestmatching Unit(BMU). Neighborhood area N_c of BMU is defined. Unit $i \in N_c$ is updated in the equation (2).

$$\boldsymbol{m}_i(t+1) \quad = \quad \boldsymbol{m}_i(t) + \alpha(t)(\boldsymbol{x} - \boldsymbol{m}_i(t)) \qquad (2)$$

where t is time, $\alpha(t)$ is a learning coefficient. The operation above is iterated until the given conditions are satisfied. The learning coefficient and neighborhood area is decreasing as the learning proceeds. After the learning, the distance in equation(1) on BMU is small enough to represent the input data class.

3.2 Input features

There is a consensus that good players are good at estimating the present phase. It is not a consensus what features they are using and which one is the most important. It is said that they might think great deal of the distribution of the pieces. We try to handle this distribution for phase classification. Table 2 shows the selected features for the input of SOM. These features are modified from those in the studies by A. Kawata et al.[15]. Table 2 denotes the "Kind of Piece" and its position. For example, we treat the status different when the Black pawn is on the 8 or 9 ranks from 7 rank, 6, 5, 4 rank, respectively. Each feature is not binary; Yes or No, but represents the number of pieces. 'all' in the Table 2 means whether they exist on the whole board or may.

4 Results

These features are extracted in each step. To examine the feasibility of our approch, we have simulated using the professional players' game records. Figure 2 shows one example of the result by SOM. The number in Figure 2 is steps of moves. In figure 2, Opening is classified into the decades from 1st to 22nd move, middle phase is from 23rd to 59th move and endgame is from 60th move to the last.

We have examined using twenty game records from "Shogi nenkan" to classify the states by SOM. The 75% game records were classified three classes in number of moves order. These 3 classes represent 3 phases, Opening, middle and endgame as shown in figure 2. Analyzing in detail, there exist some difference in the breaks among the classes between the SOM clustering results and evaluations made by semi-professional players. Table 3 shows the result of comparison of classification. O − M means edge of Opening and Middle phase. M − E means Middle phase and Endgame, respectively. Difference means the difference in moves between by semi-professional player and by SOM. If the difference about five moves was allowed, half of the games are estimated correctly Opening and Middle phase by SOM. If the difference about ten moves was allowed, then half of the games are estimated Middle phase and Endgame by SOM, too.

Three classes classified by SOM are assumed to be A, B, C. When we follow the number of moves order, there

Table 2: Features used for input

Kind of Piece	Position
Black pawn	8 or 9 ranks
	7 rank
	6 rank
	5 rank
	4 rank
Black silver	Black's Zones
	Central Zones
	White's Zones
Black promoted silver	White's Zones
Black gold	Black's Zones
	Central Zones
	White's Zones
Black king	Central Zones
	White's Zones
Black piece	Black's Zones
White piece	
Black promoted bishop and promoted rook	all
Black pawn	in hand
Black piece other than pawn	
Black silver and gold	
Threatened pieces to take	all
Black gold	24 squares adjacent to the king
Black silver	
Black piece	
White piece effect	8 squares adjacent to the king
Black piece	48 squares adjacent to the king
Black knight effect	5-9 ranks
Black knight effect	1-4 ranks

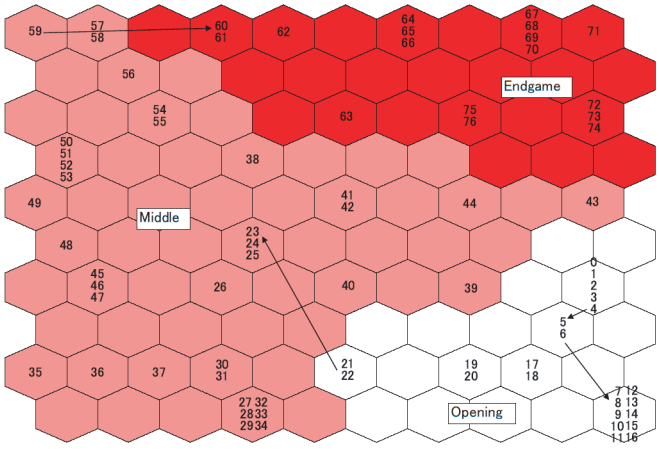

Figure 2: Sample Map 1

Table 3: Comparison of classification by semi-professional player with one by SOM

Difference	O − M	M − E
1,2	5	5
5	4	1
10	4	5
15	1	5
otherwise	5	5

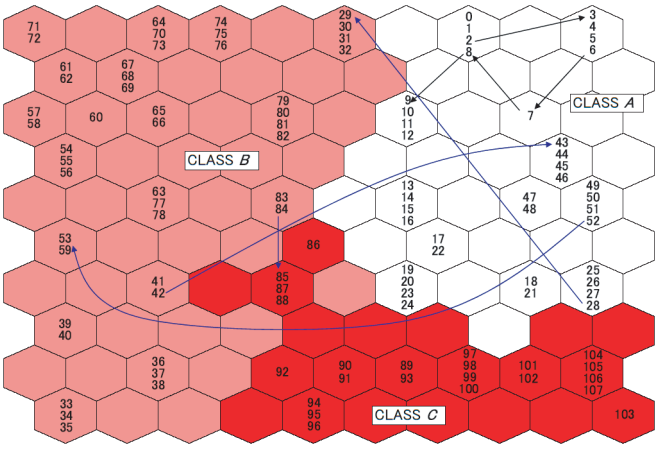

Figure 3: Sample Map 2

were five game records such that A → B → A → B → C. For example, in Figure 3, there are from 1st to 28th moves in CLASS A, from 29th to 42nd moves in CLASS B, from 43rd to 52nd moves in CLASS A again, from 53rd to 84th moves in CLASS B, from 85th moves to end in CLASS C.

5 Conclusion

We have examined the twenty professional players' records to classify the game phase by SOM. In many cases, SOM classified the phase into three stages. The three phases were dominant as expected. It should be noted that the classification depends on the content of the square rather than the number of moves. In other world, the classifications have been done through the flow of moves, and thereby would enables us to call the three phases 'opening', 'middle' and 'endgame'.

However the features used here seems to be too many for classifying the phases. The study about an autonomous extraction of the necessary features from the data is required.

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