# Evaluation Function for Siguo Game Based on Two Attitudes

ZhengYou Xia, YongPing Zhu, and Hui Lu

Department of computer science, Nanjing University of Aeronautics and Astronautics
zhengyou_xia@yahoo.com

**Abstract.** Siguo game is a fascinating imperfect information game that provides a new testbed for AI. We have written a computer program that plays Siguo game. This paper reveals and discusses the method that is based on optimistic and cautious attitudes to construct evaluation function of our system. We also present the worth and rank of material and analyze several features of evaluation function, which are piece capture, position domain of piece and oriflamme guard. Each feature of evaluation function is evaluated by general and optimistic algorithm, respectively.

## 1 Introduction

Games can model some elements of the real world, and offer more exploring methods for dealing with uncertainty. Indeed, the difficulties associated with handling incomplete or uncertain information are now receiving an increasing amount of attention in many other computer science research domains.The study of games like poker, bridge and Siguo game [1][2] could be highly valuable. Siguo, Poker and Bridge provide an excellent test bed for studying decision-making under conditions of uncertainty. There are many benefits to be gained from designing and experimenting with poker and Bridge programs [3][4]. The Siguo game can be classified two kinds (i.e. 1vs1 and 2 vs 2 model). Siguo game is an imperfect-information game, which is different to Poker or Bridge game. Siguo game can obtain less information than poker acquires during playing game. The player of Siguo game cannot get exact type information of the confederate and opponents’ piece from the previous rounds and only get results of “>”,”<”and “maybe equal”. It involves very lacking information: the premises, process and the consequences of a decision are vagueness, imprecision, and uncertainty. Therefore, Siguo game is a new test bed for AI, which is a game of imperfect information, where competing players must deal with possible knowledge, risk assessment, and possible deception and leaguing players have to deal with cooperation and information signal transmission.

As the conventional game, the evaluation function is very important for designing the senior intelligent Siguo game system and is used to estimate the players' winning chance in positions at the leaves of game-trees. The conventional games (e.g. go, chess, amazons, and Othello games, etc.) are based on the perfect information and the score of position evaluation can be exact gotten. Related works about evaluation function of these games [5][6][7][8][9][10] have been well achieved. However, since

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the Siguo game is different to traditional game, the method to construct evaluation function may be different to previous methods. In this paper, we reveal and discuss the evaluation function of our Nhope system. We define the worth and rank of material and analyze several features of evaluation function, which are piece capture, position domain of piece and oriflamme guard, respectively. We use these features to introduce the method to construct evaluation function of Siguo game. The method is based on two attitudes (i.e. optimism and pessimism) to evaluate the score of strategy.

## 2 Worth and Worth Rank of Material in the Siguo Game

In Siguo game[1], every player has twenty-five pieces. To express conveniently, we denote the Sapper, Second Lieutenant, Captain, Major, Lieutenant Colonel, Colonel, Senior Colonel , Lieutenant General, Marshal ,Mine, Bomb as $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, $x_6$, $x_7$, $x_8$, $x_9$, $x_{10}$, $x_{11}$, respectively. In the Siguo game, every material worth should be abode the experience rules of equation 1.

$$\begin{aligned} & x_9 > (x_7 + x_{11}); x_9 < (x_8 + x_{11}); x_8 \leq (x_7 + x_{11}); x_7 \geq x_{11} \\ & x_{11} \geq x_6; x_8 \geq (x_6 + x_{11}); x_9 \geq (2x_6 + x_{11}); x_1 \geq x_{10}; x_1 \geq x_5 \\ & x_1 \leq x_6; x_6 \leq 2x_5; x_5 \leq 2x_4; x_4 \leq 2x_3; x_3 \leq 2x_2 \end{aligned} \tag{1}$$

For example, in the equation 1, $x_9 > (x_7 + x_{11})$ denotes that the value of marshal material is more than the sum value of Senior Colonel and bomb material. Similarly, $x_9 < (x_8 + x_{11})$ denotes that the value of marshal material is less than the sum value of Lieutenant General and bomb material. In the Siguo game, worth of the Second Lieutenant material is suggested to be 1 (i.e. x1=1) and Worth of other materials are inferred and suggested as the follows.

$$\begin{aligned} & worth(x_1) = 9, worth(x_2) = 1, worth(x_3) = 2, worth(x_4) = 4, \\ & worth(x_5) = 7, worth(x_6) = 12, worth(x_7) = 20, worth(x_8) = 33, \\ & worth(x_9) = 45, worth(x_{10}) = 8, worth(x_{11}) = 19 \end{aligned} \tag{2}$$

To analyze characteristic of these materials, we give the worth rank according to characteristic of materials as follows.

$$\begin{aligned} & rank(x_1) = 1, rank(x_2) = 2, rank(x_3) = 3, rank(x_4) = 4, rank(x_5) = 5, rank(x_6) = 6 \\ & , rank(x_7) = 8, rank(x_8) = 9, rank(x_9) = 10, rank(x_{10}) = 6.5, rank(x_{11}) = 7 \end{aligned} \tag{3}$$

## 3 Features of Evaluation Function

In our Nhope Siguo system, evaluation function is composed of nine features and evaluated at the leaf node of game tree. In this paper, we only discuss four features and use these features to present the method of constructing evaluation function for

Siguo game. The four features include the piece capture, position domain of piece, oriflamme guard of opponent and oriflamme guard of computer.

### 3.1 Piece Capture

When piece $\alpha$ fights with piece $\beta$, let piece $\alpha$ be winner and piece $\beta$ be loser. If piece $\alpha$ and piece $\beta$ are not bombs or oriflamme, the piece $\alpha$ can get following score shown as equation 4 and piece $\beta$ can get score shown as equation 5.

$$score(\alpha,\beta) = worth(\beta) - \frac{|worth(\alpha) - worth(\beta)|}{e^{|rank(\alpha)-rank(\beta)|}} \tag{4}$$

$$score(\beta,a) = -score(\alpha,\beta) \tag{5}$$

In the Siguo game, computing of piece capture is different to chinese chess, chess, and other games that the winner can get the score that is worth of loser' piece during fight. However, in Siguo game, when the piece of winner kills piece of opponent, the type information about piece of the winner is leaked and opponent of the winner can know the exact type scope of winner' piece. To detect type scope of the opponent' piece by using suitable piece to fight with very fuzzy and uncertain opponent' piece is general method for players of Siguo game. Therefore, loser can get some worth from fight because loser can get some type information about piece of winner. Similarly, the winner loses some worth because winner expose type of itself piece to opponent during fight. In equation 4, $\frac{|worth(\alpha) - worth(\beta)|}{e^{|rank(\alpha)-rank(\beta)|}}$ is the worth that the loser can get from fight and the winner loses during fight.

When piece $\alpha$ fights with piece $\beta$, let piece $\alpha$ be bomb and piece $\beta$ be non-bomb or non-oriflamme piece. The piece $\alpha$ can get the following score shown as equation 6 and piece $\beta$ get score shown as equation7.

$$score(\alpha,\beta) = (worth(\beta) - worth(\alpha)) - \frac{|worth(\alpha) - worth(\beta)|}{e^{|rank(\alpha)-rank(\beta)|}} \tag{6}$$

$$score(\beta,\alpha) = -score(\alpha,\beta) \tag{7}$$

If piece $\alpha$ and piece $\beta$ are the same type, $score(\beta,\alpha) = score(\alpha,\beta) = 0$.

If any pieces can capture oriflamme of opponent, the piece will get score $+\infty$ and the game is over.

In our Nhope system, we use two attitudes to compute piece capture, which are optimistic and cautious attitudes. The algorithm about piece capture is illustrated as Fig1. Let $\psi_{oca}$ be the score by using optimistic capture algorithm and $\psi_{gca}$ be the score by using general capture algorithm. We order $\psi_{oca}$ and $\psi_{gca}$ by score (i.e. $\min(\psi_{oca},\psi_{gca}), \max(\psi_{oca},\psi_{gca})$ ). We can assume that the score of piece capture is

General Capture algorithm

Let $\alpha$ be piece of computer system and $\beta$ be piece of human player

1. Make the type membership set of piece $\beta$ to do unitary process and $\sum_{i=1}^{12} w_i = 1$.
2. General capture score ( $\psi_{gca}$ ) = $\sum_{i=1}^{12} w_i * score(\alpha, \beta)$ .

Optimistic Capture algorithm

1. Search the max membership value from type fuzzy set of piece $\beta$ .
2. If only one maximal type membership value can be found and the type is $\beta\_T_i$ , the optimistic capture= $score(\alpha, \beta\_T_i)$ .
3. If there are $l$ ( $l > 1$ ) different types $\Phi$ that have the same membership value and are the maximal value in the type fuzzy set of piece $\beta$ , the optimistic capture score ( $\psi_{oca}$ )= $\sum_{T_i \in \Phi} score(\alpha, \beta\_T_i) \Big/ l$

**Fig. 1.** Algorithms for piece capture

in $[\min(\psi_{oca}, \psi_{gca}), \max(\psi_{oca}, \psi_{gca})]$. In other words, we can use the two algorithms to compute the score of piece capture and the score is between $\min(\psi_{oca}, \psi_{gca})$ and $\max(\psi_{oca}, \psi_{gca})$ . $R_{capture} = [r^1_1 = \min(\psi_{oca}, \psi_{gca}), r^2_1 = \max(\psi_{oca}, \psi_{gca})]$ is called the score of piece capture.

## 3.2 Position Domain of Piece

The goal of the Siguo game is to capture opponent' oriflamme or kills out opponent' pieces that can move. To achieve the goal, player often moves piece to fight with the opponent' piece or occupy good position during playing Siguo game. To evaluate the piece capture has been discussed in the above section. In this section, we discuss evaluation about position of piece.

Definition **conjoint piece** $cp(a,b), a \text{ and } b \text{ denote piece}$ : if the position of piece $a$ is empty and piece $b$ can be moved to the position of piece $a$ by next move, then piece $b$ is conjoint to piece $a$ .

Definition **position domain of piece** $a$ , $pdp(a,\Theta), \Theta$ *denotes position domain* : $\exists b_i$ piece, $i \in (1, \cdots n)$ , if $b_i$ satisfies $cp(a,b_i)$ , then $b_i \in \Theta$ . If

$\{a, b_i\} \subseteq \Theta$ *and* $\{a, b_i\} \supseteq \Theta, i \in (1, \ldots \cdots n)$,then $pdp(a, \Theta)$ is called position domain of piece $a$.

Fig2a and Fig2b show position domain of senior colonel piece of player 1. In the domain, black piece with unknown type is piece of player 2. In the Siguo game, more fifty moving strategies can be generated for every piece of sapper type. If every piece is considered to be possible sapper, the moving strategies will increase explosively. Therefore, in our Nhope Siguo system, if the membership value of sapper type is maximal in the type fuzzy set of opponent' piece, we consider the piece as piece of sapper type to avoid every piece as the piece of sapper type. We assume the computer system moves SC to the position that shown as in Fig2a and Fig2b. Therefore, in the Fig2a, the position domain of SC is $pdp(SC, \Theta) = \{\text{B,SC,1st piece,3rd piece,4th piece}\}$. In the Fig2b, since membership value of sapper type in the 1st piece is maximal, we consider the piece as sapper, which can fly to position of SC.Therefore, we consider the 1st piece is neighboring to SC and the position domain of SC is $pdp(SC, \Theta) = \{\text{B,SC,1st piece,4th piece}\}$.

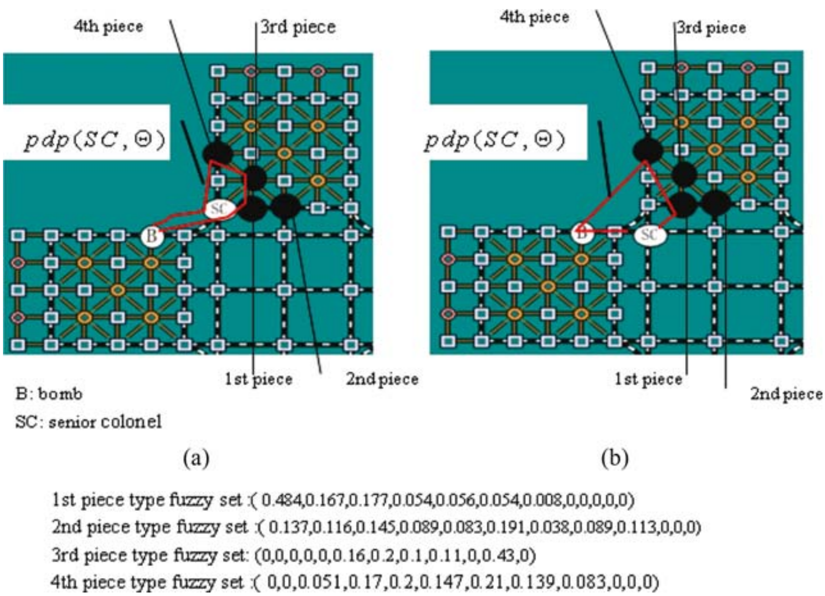


**Fig. 2.**(a) Piece position domain (b) Piece position domain

When one player moves a piece to one position, we evaluate the quality of the position by analyzing the position domain of the piece according to several features such as safety, joint defense, etc. We present an algorithm for evaluation of position domain of piece based on two attitudes that are optimistic and cautious attitudes. The general algorithm for evaluating position domain of piece is presented in the Fig3. If we use Optimistic Capture algorithm instead of General Capture algorithm in the Fig3, general algorithm for evaluating position domain of piece in the Fig3 becomes optimistic algorithm for evaluating position domain of piece. Similarly, let $pdp(a,\Theta)_{general}.sq$ be the score of position domain of piece $a$ by using general algorithm for evaluating position domain of piece and $pdp(a,\Theta)_{optimistic}.sq$ be the score of position domain of piece $a$ by using Optimistic algorithm for evaluating position domain of piece. The score of position domain of piece $a$ is $R_{pdp} = [r^1_2 = \min(pdp(a,\Theta)_{optimistic}.sq, pdp(a,\Theta)_{general}.sq)$ $, r^2_2 = \max(pdp(a,\Theta)_{optimistic}.sq, pdp(a,\Theta)_{general}.sq)]$

1. Check conjoint piece of piece of player1 and build position domain of piece $\alpha : pdp(\alpha,\Theta)$.The pieces of player 1 in the $pdp(\alpha,\Theta)$ are marked as $o\alpha_i.sq = 0, i \in (1...n)$.
2. If there is not any piece of opponent in the $pdp(\alpha,\Theta)$,return.
3. If the piece $o\alpha_i$ is in the arm camp, then set the security quality of piece $o\alpha_i.sq$=0.25
4. Else,use the General Capture algorithm to compute, $\psi_{gcc}^{\beta_j}.\alpha_i = \sum_{k=1}^{12} w_i * score(o\alpha_i,\beta_j), j \in (1...l),\beta_j$ satisfy cp($o\alpha_i,\beta_j$), $\beta_j \in pdp(\alpha,\Theta) and \beta_j$ is piece of player 2 .
5. Choose the minimal value from $\psi_{gcc}^{\beta_j}.\alpha_i$ and $o\alpha_i.sq$=min($\psi_{gcc}^{\beta_j}.\alpha_i$), $j \in (1...l)$
6. until the computation of $o\alpha_i$ pieces have been finished
7. If $o\alpha_i, i \in (1,...n)$ are all positive or negative, choose the minimal value from $o\alpha_i.sq$ and $pdp(\alpha,\Theta).sq = min(o\alpha_i.sq)$. Return pdp$(\alpha,\Theta).sq)$
8. Choose pieces of player 1, and they are marked as $l\alpha_k \in, k \in (1,...m)$ ,$l\alpha_k \in pdp(\alpha,\Theta), l\alpha_k \subseteq (o\alpha_i) and l\alpha_k.sq \geq 0$.
   (a) Search $s\alpha_j$,it satisfies cp($l\alpha_k, s\alpha_j$),$s\alpha_j \neq bomb, s\alpha_j \subseteq o\alpha_i and s\alpha_j.sq < 0, j \in (1,...n_1)$
   8.1.1 Search piece $\beta_k$ of player2, the $\beta_k$ satisfies min($\psi_{gcc}^{\beta_k}.\alpha_j$), $k \in (1,...l)$ /* for optimistic algorithm, $\beta_k \neq bomb$ */
   8.1.2 If $l\alpha_k.sq > o and l\alpha_k = bomb$,then goto (b)
   8.1.3 Compute $F = \sum_{i=1}^{12} w_i * score(l\alpha_k,\beta_k)$,compute $G_{s\alpha_j}^{l\alpha_k} = F + s\alpha_j.sq$
   8.1.4 If the check of $s\alpha_j$ is not finished ,then goto 8.1.1
   (b) If the check of $l\alpha_k$ is not finished ,then goto (a)
9. $s\alpha_j.sq = max(G_{s\alpha_j}^{l\alpha_k}), k \in (1,...m), j \in (1,...n_1)$
10. $pdp(\alpha,\Theta).sq = min(s\alpha_j.sq), and return(pdp(\alpha,\Theta).sq)$

**Fig. 3.** Algorithm for analyzing position domain of piece

### 3.3 Oriflamme Guard

In the Fig4, the 2k, 3j and 2i positions around the oriflamme are called external guard position, and the 1k, 2j and 1i positions around oriflamme are called interior guard position. When no any self-pieces are on external guard position or interior guard position and these positions are exposed to opponent, we consider guard position danger.

Two methods can be used to analyze the dangerous degree about guard position of oriflamme, which are methods of static and dynamic analysis. For static analysis, only six guard positions of oriflamme are considered in constructing evaluation function. However, dynamic method is too complex and performance of system will be worse because plenty of pieces that can arrive to guard position of oriflamme in next move

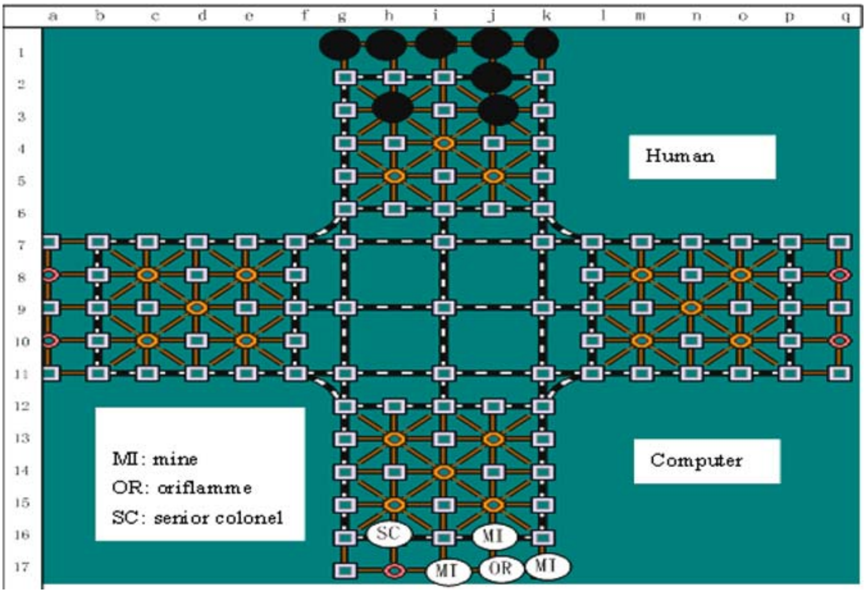


**Fig. 4.** Oriflamme guard

must be considered. In our previous version of Nhope system, the result of system performance is not good by using dynamic analysis method. Therefore, in this paper, we only discuss the static method to analyze guard position. The equation8 and 9 are experience equations for evaluating dangerous degree about external guard and interior guard position. If there are no any dangerous guard positions, we consider the guard position safety and set score of oriflamme guard zero. To compute oriflamme guard feature for computer is illustrated as in Fig5 and to compute oriflamme guard feature for human player is illustrated as in Fig6.

$$\text{external\_guard}=\frac{\text{m}}{1+\text{x}^{-2}}, x \in (1,2,3), \text{m } \textit{is suggested as} \text{ in } [8,20] \tag{8}$$

$x$ denotes the number of dangerous guard positions (i.e. 2k, 3j and 2i positions).

$$\text{interior\_guard}=\frac{\text{n}}{1+\text{y}^{-2}}, y \in (1,2,3), \text{m is } \textit{suggested as} \text{ in } [20,45] \tag{9}$$

$y$ denotes the number of dangerous guard positions (i.e. 2k, 3j and 2i positions).

## 4 Experiment About Problem of Evaluation Function

For perfect information, the evaluation function can evaluate exactly the strategy of player. However, for imperfect information game, since information about opponent is imperfect or very fuzzy and uncertain, evaluation function cannot evaluate validly

1. Check the six guard positions around computer' oriflamme
2. Check external guard positions, if the three positions are all occupied by self-pieces, then external_guard =0.
   Else check the number of dangerous external guard positions and get $x$ .
   Compute external_guard= $\frac{m}{1+x^{-2}}$ , $x \in (1,2,3)$ .
3 Check interior guard positions, if the three positions are all occupied by self-piece, then interior_guard =0.
   Else checks the number of dangerous external guard positions and gets $y$ .compute interior_guard= $\frac{n}{1+y^{-2}}$ , $y \in (1,2,3)$ .
4. $Ori\_guard$ = external_guard+interior_guard , and return ( $Ori\_guard$ ).

**Fig. 5.** Algorithm for oriflamme guard feature of computer

1. If the oriflamme position of human has been revealed, then
/* under this situation, general algorithm and optimistic algorithm is the same as the following steps*/
1.1. Check external guard positions, if the three positions are all occupied by self-pieces, then external_guard =0. Else check the number of dangerous external guard positions and get $x$ .
   Compute external_guard= $\frac{m}{1+x^{-2}}$ , $x \in (1,2,3)$ .
1.2 Check interior guard positions, if the three positions are all occupied by self-piece, then interior_guard =0. Else check the number of dangerous external guard positions and gets $y$ .compute interior_guard= $\frac{n}{1+y^{-2}}$ , $y \in (1,2,3)$ .
1.3 $Ori\_guard$ = external_guard+interior_guard , and return ( $Ori\_guard$ ).
2. There are two positions that contain oriflamme piece.
2.1 If it is optimistic attitude, then choose the position that is maximal membership value of oriflamme type between two positions. Go to 1.1 for computing oriflamme guard by using the position.
2.2 Check the two oriflamme base camp, respectively and operations are same as the above steps

$$Ori\_guard_{general} = w_{first} * Ori\_guard_{first} + w_{second} * Ori\_guard_{second}$$

Return ( $Ori\_guard_{general}$ )

**Fig. 6.** Algorithm for oriflamme guard feature of human player

strategy of player in few situations. The situation is that factual information about opponent is entirely different to that we get from model or experience data. Under the situation, evaluation function cannot well give proper score about strategy. We called the phenomena invalid problem of evaluation function.We use our Nhope system to fight with human player of 1st level, 2nd level, 3rd level and 4th level in internet Siguo game club. The rate of invalid problem of evaluation function is increased with level of human player shown as in Fig7.

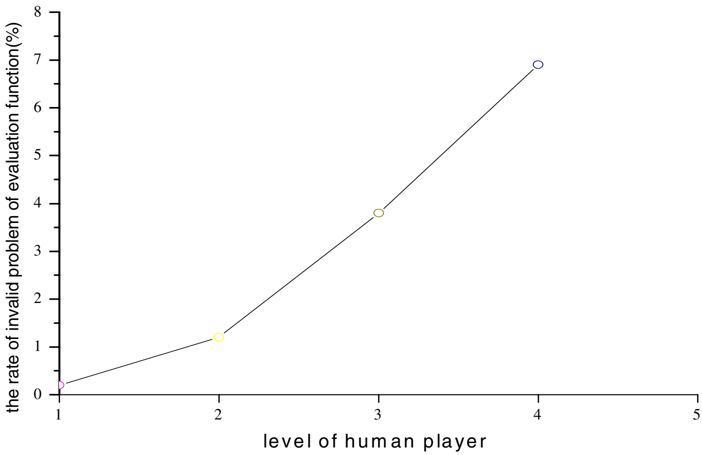


**Fig. 7.** Invalid problem level of human player

The first reason is that our system analyzes and infers type information of pieces based on statistical data that is mined from more than one thousand different lineups of Siguo game. Statistical data only shows general rules and information about opponent. The second reason is that our system assumes that behavior of human player is rational. However, good human player can disturb the judgment of our computer system by cheat. Generally, human player of high level can easily apperceive the intention of opponent of low level and very exact infer the type of piece of opponent based on psychology of opponent that is concealed in action of moving piece by opponent. For human player of low level, the ability to apperceive the intention of opponent is weak and they often move piece according to principle of piece force balance and joint defense, etc. Therefore, we can validly construct model to fight with human player of low level by using previous statistical data. Presently, the force rank of our Nhope system is equal to the second rank of human player in the two-person competition (i.e.1V1) in the internet club. However, the force rank of our system is equal to novice of human player in four-person competition (i.e.2V2).

## 5 Conclusion

In this paper, we present a novel method to construct evaluation function of our Siguo game system. An important idea in the method of constructing evaluation function is based on two attitudes, which are optimistic and cautious attitudes. To use the method, we can make score of evaluation function in rational interval and decrease invalid problem of evaluation function. However, it is not very valid to evaluate the human player of high level because sporadic invalid problem of evaluation is occurred. To improve the exact guessing type of opponent' piece can decrease validly problem of evaluation function, which is the research that we are implementing now.

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