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# Determining the Appropriate Move in Chinese Chess by Fuzzy Reasoning Model

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**Abstract**

*A dynamic fuzzy reasoning approach is proposed to infer the best next move in playing the Chinese chess game. The fuzzy cognitive map is exploited to establish the mutual relationship between the current and the target positions on the chess board. We use the guarded degrees and important degrees of the source and the target to create 36 fuzzy rules for the rule base. Among the legal moves, we can choose the one with the highest firing strength as the best next move. Different cases are presented to illustrate how satisfactory the proposed model conforms to the experts' thinking in playing the Chinese chess game.*

*Keywords*: Fuzzy cognitive map, guard heuristic, Chinese chess, fuzzy reasoning model.

## 1. Introduction

As an extension of the classical logical systems, fuzzy set theory [4] provides an effective approach for dealing with problems described in imprecise or uncertain format. The importance of fuzzy reasoning lies in that most thinking modes of human beings are approximate in nature. Therefore, how to transform the human thinking into a model which can be processed by computers becomes very important. Nowadays, fuzzy logic system has been widely applied to solving control problems [5].

Chinese chess is a very famous game which is similar to the zero-sum situation [3]. One's gain is the opponent's loss. Depending on the player's intelligence, different strategies will be taken when the same situation is faced. In designing a computer program to help decide the best move, the tree-searching method was normally used [3]. The embedded problem in the tree-searching scheme is that of time-sonsuming. In [6], we approached from the fuzzy cognitive map [2] to help players play the Chinese chess. This research is an extension of our previous work and is dedicated to apply the fuzzy reasoning method to mimiding the expert's thinking in playing the chess. Different kinds of membership functions are used to infer the results. To provide a more intelligent playing, the multi-step thinking method is also investigated.

## 2. Fuzzy reasoning model

For those who are not experts of chess game, they may decide a move to solve the current situation only. The experienced players may play in a more intelligent way. They can think more steps ahead or set up a trap to win the game.

The main purpose of guard heuristic is to obtain the guard information for each piece on the board. The guard value provides us two kinds of information: the safety of the current and target positions. A piece with unsafe status should have a higher moving priority. The safety of the target position is considered to avoid recapturing. That is, those moves that will result in a danger occured have to be prevented. Moreover, moves that allocate pieces to safer places and result in chances to capture the opponent's pieces should obtain a higher priority. To make the right decision for the next move, each intersection on the board needs to be carefully considered. A guard strength is attached to each intersection to indicate how safe or unsafe a piece faces.

To implement the concept mentioned above, a value called guard value is computed for each intersection to represent the guard strength. The basic guard value for an intersection is the sum of the capture strengths from those pieces able to move to the intersection and able to be captured. Empirically, the least valuable piece is assigned the largest capture strength. Table 1 lists the capture strengths suggested for different pieces of chess [3]. Note that an integer value has be assigned for each piece. The guard value is formulated as follows:

$WP = \{x | x \, is \, White's \, piece \, on \, board\}$

$BP = \{x | x \, is \, Black's \, piece \, on \, board\}$

$P = \{x | x \in (WP \cup BP)\}$

$S=\{x|x$ is an intersection on chess board$\}$

$$GM_W = \{(x,y) | x \in S \wedge y \in WP \wedge (y \, moves \, to \, x) \in (Guard \, Moves)\}$$

$$GM_B = \{(x,y) | x \in S \wedge y \in BP \wedge (y \, moves \, to \, x) \in (Guard \, Moves)\}$$

$$GM_W^i = \{x | (i,x) \in GM_W\}$$

$$GM_B^i = \{x | (i,x) \in GM_B\}$$

$$GV(i) = \begin{cases} \sum_{v \in GM_W^i} CS(v) + \sum_{v \in GM_B^i} CS(v) + CS(p(i)) \\ \quad if \; p(i) \neq \varnothing \wedge GM_W^i \neq \varnothing \wedge GM_B^i \neq \varnothing \\ \sum_{v \in GM_W^i} CS(v) + \sum_{v \in GM_B^i} CS(v), \; otherwise. \end{cases}$$

Table 1. The capture strength suggested for each piece.

| | General | Guard | Elephant | Warrior | Horse | Cannon | Soldier |
|---|---|---|---|---|---|---|---|
| White | +1 | +9 | +9 | +2 | +5 | +4 | +9 |
| Black | -1 | -9 | -9 | -2 | -5 | -4 | -9 |

Here, we use the fuzzy cognitive map to help us decide the best next move. Fuzzy cognitive map is employed in a feedback system to find the relationship between nodes in the fuzzy network. Kosko and Dickerson [1] showed that the basic state of a fuzzy cognitive map is a binary vector C of length n, i.e., $C = (C_1, C_2, ..., C_n)$. There are $2^n$ distinct states located at the $2^n$ corners of the fuzzy n-cube. Each state in the cube has the value in the unit interval. The fuzzy cognitive map model is to find a sequence or a smooth path inside the fuzzy cube. Applying the important concept of fuzzy cognitive map to the chess system, we can calculate the state of a fuzzy cognitive map as follows:

$$C_i(t+1) = \sum_{j=1}^{n} w_{ij}(t) C_j(t), \qquad (1)$$

In Eq.(1), $w_{ij}$ represents the weight going from the jth node to the ith node. $C_j(t)$ is the current status of the jth node. Note that a node in a fuzzy network corresponds to a chess on the chess board. The weight $w_{ij}$ in Eq.(1) corresponds to the chess mutual relationship on the board and is defined as follows:

$$w_{ij} = \lambda \frac{lastno}{total \times stepno}, \qquad (2)$$

where *lastno* is the number of pieces left on the board, *total* is the total number of pieces appeared at the beginning, *stepno* is the number of steps needed to move from the jth to the ith positions, and λ is the adaptive learning rate. We then use both Eqs.(1) and (2) to decide the guard value for each position on the board. Define ε as the tolerant error. If the ending condition

$$C_i(t+1) - C_i(t) < \varepsilon \qquad (3)$$

is satisfied or a predefined iteration number is met, then we quit the network. Since it is not that easy to meet the constraint given in Eq.(3) in a short time, in this research we just iterate five times and then stop the network. Fig. 1 gives the guarded relationship between pieces on the board.

The guard values obtained from above will provide the guard information for each intersection on the board. The information indicates whether an intersection is guarded by one's pieces or not. Based on the guard values we can build a correlational matrix for the pieces on board for dynamic prediction. Then we use the rule-based reasoning model to infer the appropriate next move.

## 3. The rule-based reasoning model

After constructing the guard matrix and assigning each piece a guard value, we can find all legal moves on the board. To provide the player a final decision, we approach from the rule-based reasoning model to obtain the firing strength of each legal move. The proposed parallel processing architecture is shown in Fig. 2.

The fuzzy rule base contains a number of fuzzy rules. Each rule has the type as follows:

If $X_1$ is A(1) and $X_2$ is A(2) and $X_3$ is B(1) and $X_4$ is B(2), then Y is RV.

In the proposed fuzzy rule, $X_1$, $X_2$, $X_3$, $X_4$, and RV represent the guarded degree of the source, the guarded degree of the target, the importance of the source, the importance of the target, and the reasoning value, respectively. Five terms, i.e., *low*, *mid-low*, *medium*, *mid-high*, and *high*, are assigned for the guarded degree, while only three labels, i.e., *low*, *medium*, and *high*, are used for the important degree. As a result, at most 225 rules may be generated in the fuzzy rule base.

In this research, however, we use only 36 subjectively selected rules as listed in Table 2 to infer the outcome. Each bell-shaped membership function is defined as follows:

$$\mu(x) = \exp(-(\frac{x-c}{a})^2). \quad (4)$$

In Eq.(4), parameters $a$ and $c$ control the shape of the membership function. In this paper, the triangular and the Gaussian shapes of membership functions are also considered and similar simulation results have also been obtained.

To determine the best next step from all of the legal moves, the following algorithm is considered:

(1) use the product operation to decide the firing strength of each rule, i.e.,

$$R_i = \mu_{A(1)} \otimes \mu_{A(2)} \otimes \mu_{B(1)} \otimes \mu_{B(2)}. \quad (5)$$

(2) normalize the firing strength of each rule:

$$R_i' = \frac{R_i}{\max_{j=1}^{36} R_j}. \quad (6)$$

(3) summarize the firing strenth:

$$RV_j = \sum_{i=1}^{36} R_i. \quad (7)$$

(4) find the maximum value among all of the legal moves to determine the best next move:

$$RS = \max_{i=1}^{m} RV_i, \quad (8)$$

where m represents the number of legal moves.

Table 2. The 36 rules generated for determining the firing strength. Note that H, M, and L represent high, medium, and low, respectively.

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| x1 | H | H | H | H | L | L | L | L | H | H | H | H | L | L | L | L | M | M |
| x2 | L | L | L | L | H | H | H | H | H | H | H | H | L | L | L | L | M | M |
| x3 | L | H | L | H | L | H | L | H | L | H | L | H | L | H | L | H | L | H |
| x4 | H | L | L | H | H | L | L | H | H | L | L | H | H | L | L | H | H | L |
| con | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 | R16 | R17 | R18 |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| x1 | M | M | L | L | L | L | H | H | H | H | M | M | M | M | M | M | M | M |
| x2 | M | M | M | M | M | M | M | M | M | M | L | L | L | L | H | H | H | H |
| x3 | L | H | L | H | L | H | L | H | L | H | L | H | L | H | L | H | L | H |
| x4 | L | H | H | L | L | H | H | L | L | H | H | L | L | H | H | L | L | H |
| con | R19 | R20 | R21 | R22 | R23 | R24 | R25 | R26 | R27 | R28 | R29 | R30 | R31 | R32 | R33 | R34 | R35 | R36 |

In our proposed model, we have considered all of the effective factors and have adopted the product operation to infer the firing values for each rule. Assume that all fired values for all rules are equally important, we can obtain the strongest strength from all legal moves. As a result, the most appropriate next move can be easily decided.

## 4. Simulation results

Refer to Fig. 3, the relative chess positions on the board are shown. Before performing the simulation to verify the effectiveness of the proposed model, the guard value matrix given in Table 3 has to be constructed first. Besides, the firing strength from each rule listed in Table 2 must be calculated.

Assume that it is the Black's turn in Fig. 3. After calculating the firing strength for each legal move, we found that the maximum value is 3.003659. This corresponds to the move from (row 4, column 3) to (row 6, column 2). It means that the Black Horse at position (row 4, column 3) will capture the White Cannon at position (row 6, column 2). This is a quite obvious outcome. Besides, after capturing the White Cannon, the Black Horse will be further protected by the Black Warrior and will not result in any immediate danger. Any experienced player will select the Black Horse to capture the White Cannon if such an opportunity is given.

Similarly, from Fig. 4 we found that the maximum guard value for the Black side is 2.485725. It means that the best next move for the Black's is from (row 7, column 2) to (row 9, column 3). This corresponds to move the Black Horse back to a safe place. Another choice is to select Black Cannon to capture the White Horse. Although may result in capture by the other White Horse in the next step, the Cannon is considered to be less important than the Horse in Chinese chess. Thus, using the Black Cannon to capture a White Horse is not a bad one.

In Fig. 5, we found that the maximum guard value for the Black side is 1.651162. It means that the best next move for the Black's is from (row 3, column 2) to (row 7, column 2). This corresponds to select Black Warrior to capture the White Cannon. After capturing the White Cannon, the Black Warrior can by the way protect the Black Horse from capturing by the White Warrior. Thus, using the Black Warrior to capture a White Cannon should be an intelligent decision.

Table 3. Fuzzy guard value matrix derived from Fig. 3.

| | col 0 | col 1 | col 2 | col 3 | col 4 | col 5 | col 6 | col 7 | col 8 |
|---|---|---|---|---|---|---|---|---|---|
| row 0 | -1.50 | -2.30 | -6.93 | -7.61 | -3.66 | -10.63 | -6.83 | -5.96 | -3.52 |
| row 1 | -1.64 | -3.65 | -5.77 | -6.09 | -12.55 | -6.67 | -5.60 | -1.28 | -5.30 |
| row 2 | -4.96 | -5.56 | -3.37 | -5.03 | -7.48 | -6.87 | -3.44 | -6.04 | -7.18 |
| row 3 | 1.01 | -4.69 | -5.91 | -4.99 | -4.81 | -3.59 | -4.68 | -3.44 | -3.20 |
| row 4 | -0.81 | -4.81 | -6.65 | -6.12 | -1.97 | -6.78 | -9.41 | -3.37 | -1.75 |
| row 5 | 0.66 | 4.51 | 5.03 | -0.44 | -1.53 | -3.85 | 5.47 | -1.38 | -1.86 |
| row 6 | 2.95 | 0.37 | 5.90 | 3.59 | 5.55 | 6.34 | 3.87 | 4.92 | 0.51 |
| row 7 | 8.82 | 0.76 | 1.69 | 7.30 | 7.96 | 6.06 | 3.17 | 5.10 | 5.38 |
| row 8 | 4.85 | 0.95 | 3.91 | 3.44 | 9.34 | 2.82 | 6.63 | 2.75 | 2.21 |
| row 9 | 2.71 | 1.88 | 5.98 | 9.89 | 1.71 | 5.54 | 7.35 | 4.17 | 1.60 |

## 5. Multi-step reasoning

To mimid the expert's playing mode, the multi-step reasoning method is investigated in this section. We consider two-level reasoning model to infer the best next move. From the multi-step reasoning model we can infer the desired next move backwards. Fig. 6 shows the proposed reasoning structure. The first level selects the highest and second highest firing values to reason individual best next move. The second level repeats the same work as the first one. As a result, the most appropriate next move can be inferred backwards.

Fig. 7 depicts the experimental results from the chess board given in Fig. 5. Taking a look at Fig. 7 we found that the best move in the first level is from (row 3, column 2) to (row 7, column 2), as verified in section 4. In the second level, the fourth legal move is also from (row 3, column 2) to (row 7, column 2), which is exactly the same as from the first level. This means that the firing value will have a recursive outcome, that is, while going to the second level, the system will infer the best firing value which equals to the first level's. Results from the multiple reasoning model also verify the efficiency of the proposed reasoning approach.

## 6. The design of users interfaces

To allow the users to have fun in playing the chess game, we implemented the fuzzy Chinese chess by the C++ language. Users can choose two different kinds of playing modes, i.e., playing with the opponent or with the computer. Fig. 8 shows the graphical interface for the players to select the playing modes. Our system also allows the players to select the *red* or *black* side to play and which side to start first.

Fig. 9 displays the chess system at the beginning of play. In designing such a system, all the legal moves and other restrictions should be carefully considered to prevent the users from taking the wrong steps. In case an illegal step is attempted, an error message will appear on the dialogue box. Besides, if the general is locked by the opponent, an alarm message should be given. Since our fuzzy reasoning model is good for the middle of the game, the chess system is still under testing.

## 7. Conclusion

The fuzzy cognitive map was used to dynamically change the the guard value of each intersection on the board to generate the guard matrix. To determine the best next move, a rule-based model is presented to find the strongest strength from the fired rules. Instead of using the conventional tree searching method, the fuzzy inference mechanism is widely considered to infer the next move. As a result, the time spent to find the best next move is shorter than the tree-searching method and the legitimacy of each move is increased. Three different chess situations are simulated to infer the best next move and the results coincide with the experienced players' thinking. To verify the efficiency of the proposed scheme, the two-step ahead reasoning model is also investigated.

## Acknowledgment

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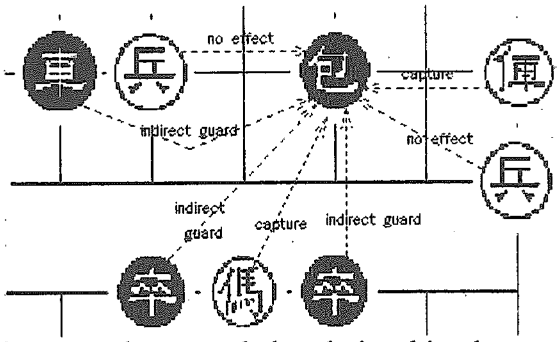


Fig. 1. The guarded relationship between pieces in Chinese chess game.

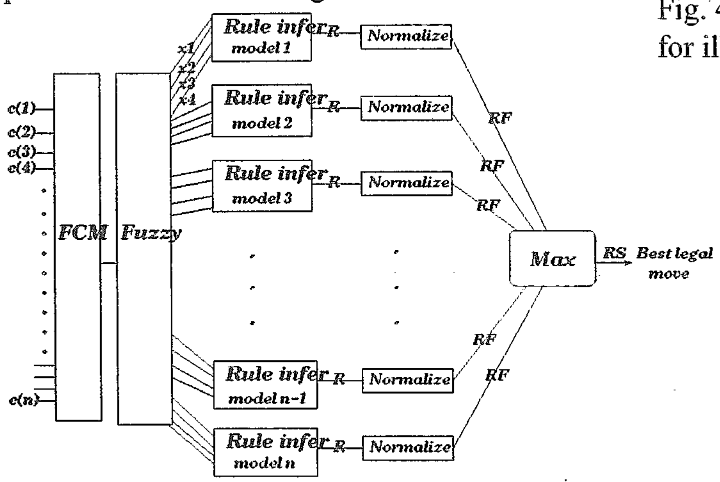


Fig. 2. The parallel structure used to derive the best next move.

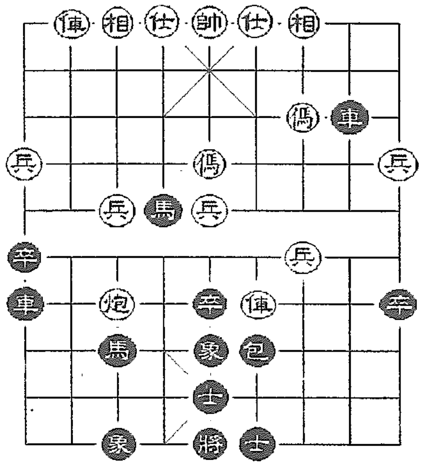

Fig. 3. The first chess positions arranged for illustration.

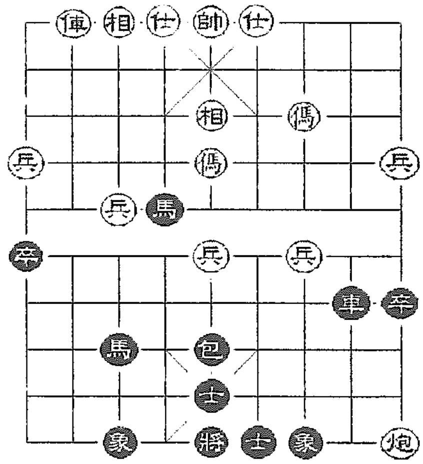

Fig. 4. The second chess positions arranged for illustration.

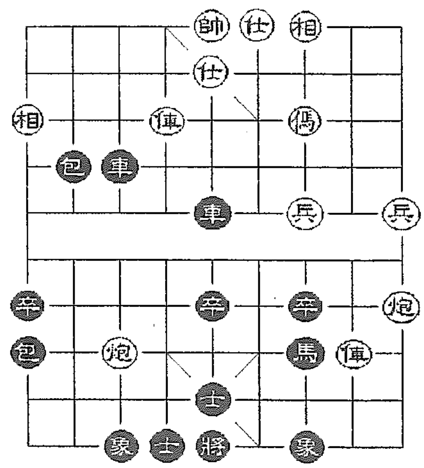

Fig. 5. The third chess positions arranged for illustration.

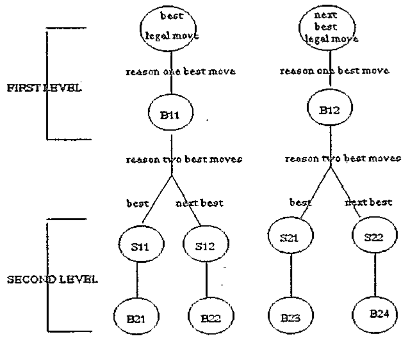


Fig. 6.The two-step ahead reasoing structure.

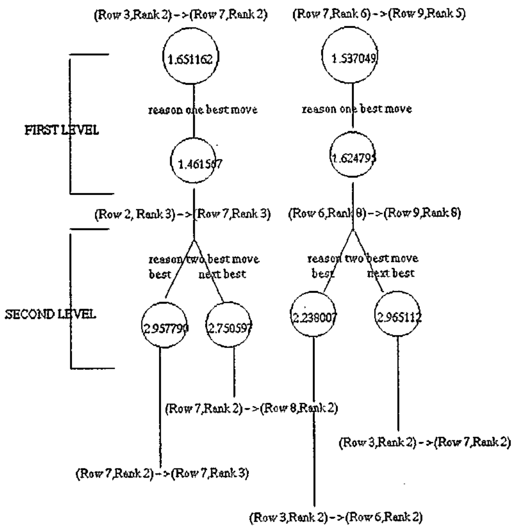


Fig. 7. The experimental results from the multi-step reasoning model.

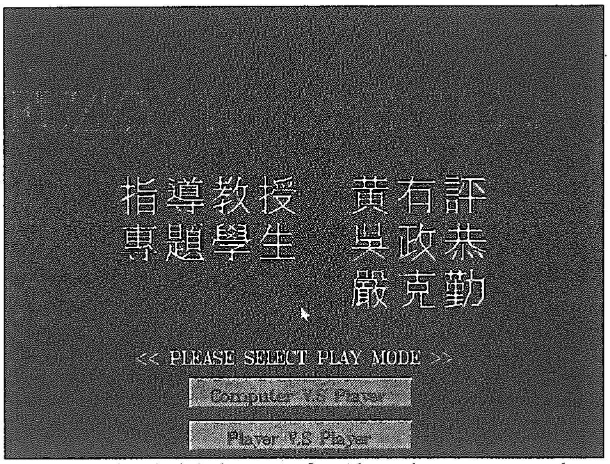


Fig. 8. The initial state for the players to select the playing modes.

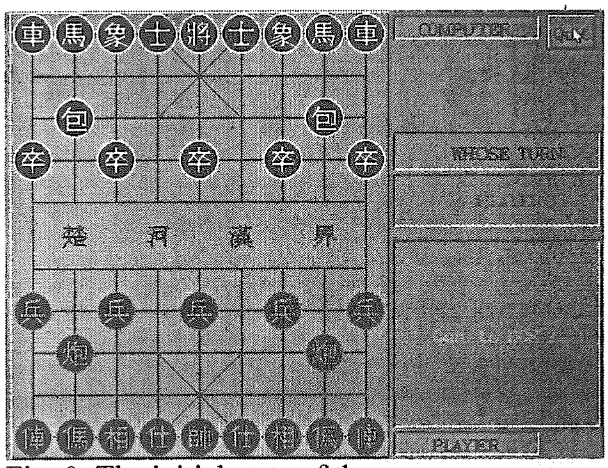


Fig. 9. The initial state of the game.