Fuzzy Chess Tactics♦

João Paulo Carvalho[1,3], Nuno Cavaco Horta[2,3], Daniel Chang Yan[1,3], Pedro Ramos e Silva[3]

1: INESC-ID - Instituto de Engenharia de Sistemas e Computadores

2: IT – Instituto de Telecomunicações

3: IST – Instituto Superior Técnico

R. Alves Redol, 9, 1000-029 Lisboa, PORTUGAL

Phone: +351.1.3100262 Fax: +351.1.3145843

E-mail: joao.carvalho@inesc-id.pt, nuno.horta@gcsi.ist.utl.pt, dnlcy@sapo.pt

Abstract

This paper presents Fuzzy GenChess, a fuzzy implementation for the tactics of the game of chess. Fuzzy GenChess models chess expert knowledge and uses an extension of fuzzy TPE systems to compute a fuzzy evaluation function for each chess piece in each play.

Keywords: *Chess tactics, fuzzy chess knowledge, fuzzy chess evaluation function*

1 Introduction

This paper presents a fuzzy implementation for the tactics of the game of chess. Chess as been traditionally used for explaining fuzzy reasoning, and is often considered a platform of choice to test intelligent systems. However, an extensive search for applications of fuzzy sets, inference or reasoning to the game of chess, gives hardly any concrete results. One can find fuzzy improvements to classic tree search algorithms like, for example, fuzzy forward-pruning (which can obviously be applied to chess), but not a single relevant result in what concerns applying fuzzy to express or implement human chess knowledge. It is a fact that, chess, the ultimate measure of “intelligence” in old times, seems to have shed some of its gloss once it was discovered that you can do it quite well with alpha-beta pruning and a lot of sheer calculating power. However, chess knowledge is still arguably one of the factors that make good human chess players so hard to be beaten by a machine as long as time is not an issue - for instance, in e-mail based tournaments, humans have a large advantage over machines and their expertise is the defining winning factor.

The work we present here is part of an ongoing project called GenChess [6][8] that intends to use the game of chess as a platform to compare intelligent computing techniques. This particular part of the project is dedicated to represent chess expert common sense tactics using fuzzy systems. Examples of these kind of knowledge include sentences like "the knights should dominate the board centre", or "the king should be kept protected in the borders until mid game, but must privilege the centre during end game".

2 Implementation

Our first approach to the implementation of Fuzzy Chess tactics [6] was based on a classic Fuzzy Rule Based system, where each board piece was evaluated using a n-input fuzzy rule base, and where all variable linguistic terms and membership functions had no restrictions. As a result, the system had a large number of rules and although it provided interesting results concerning the evaluation of the board, it was too slow when compared to systems with simpler evaluation functions but able to make deeper searches in the same amount of available time. The trade off between better evaluation and speed was not good enough for the fuzzy system to win on a consistent basis when a time-limit was involved. Therefore, the most recent Fuzzy GenChess developments focused on obtaining a faster fuzzy inference system. The used approach was based on an extension of Sudkamp and Hammell’s single input TPE Systems (Triangular-Partition Evenly Systems) [7].

2.1 Two-input TPE systems

Sudkamp and Hammell’s TPE systems [7] provide a way to accelerate the fuzzy inference procedure in 1-input fuzzy systems. It also makes the inference process independent from the number of involved linguistic terms, since instead of a sequential application of all rules in a rule base, it allows the direct access to the relevant rules using an indexation process, and infers the rule result using previously computed constants. This approach is possible due to restrictions imposed on the involved linguistic terms: all membership functions must be triangular, complementary, and evenly spaced in the universe of discourse (UoD). Figure 2 shows an example of a possible set of linguistic terms in a TPE system.

♦ This work is partially supported by Fundação ORIENTE – Portuguese Orient Foundation

However, Sudkamp's approach could only be used in 1-input systems, and would be useless when applied to the Fuzzy Chess tactics due to the higher number of input parameters.

In order to apply TPE's to Fuzzy GenChess, we had to generalize the TPE approach to multi-input systems. We concluded that 2-input TPE systems are still feasible and adequate to our problem [8], but systems with a larger input number, even if possible, are too complex and stop complying with the goal of obtaining a faster fuzzy inference mechanism. The next paragraphs provide a brief explanation and show the main results regarding 2-input TPE systems. Details can be seen in [8], and will be submitted for publication on a near future.

Any 2-input fuzzy system rule base with n-linguistic term variables can be represented as a 2 dimensional table. Table 1, represents an excerpt of a generic 2 input fuzzy rule base.

Table 1 – An excerpt of a 2-input Fuzzy Rule Base

	A_i	A_{i+1}
B_j	C_r	C_t
B_{j+1}	C_s	C_u

$$if\ \ X\ \ is\ A_i\ and\ Y\ is\ B_j\ then\ Z\ is\ C_r$$
$$if\ \ X\ \ is\ A_i\ and\ Y\ is\ B_{j+1}\ then\ Z\ is\ C_s$$
$$if\ \ X\ \ is\ A_{i+1}\ and\ Y\ is\ B_j\ then\ Z\ is\ C_t$$
$$if\ \ X\ \ is\ A_{i+1}\ and\ Y\ is\ B_{j+1}\ then\ Z\ is\ C_u$$

Due to the characteristics of TPE's membership functions (mbf), and assuming a weighted-averaging defuzzification process, it is possible to directly obtain the result of a given inference from the equations that describe the mbf, the even division of the input space, and the indexation of each input value to a given interval. For 2-input TPE systems, the inference result, z, can be obtained by applying 1 of 4 equations that assume the following format:

$$z = \frac{yH_1 + H_2 + xH_3 + H_4}{yH_5 + H_6 + xH_7 + H_8}$$

where all H_i are previously computed constants that depend on the mbf equations, on the intervals, and on the (crisp) membership of the input values to 1 of 4 different areas (Figure 1).

As long as all H_i are previously computed, and with proper indexation of the input values, it is possible to obtain a very fast fuzzy inference process that is independent of the number of linguistic terms in each involved fuzzy variable.

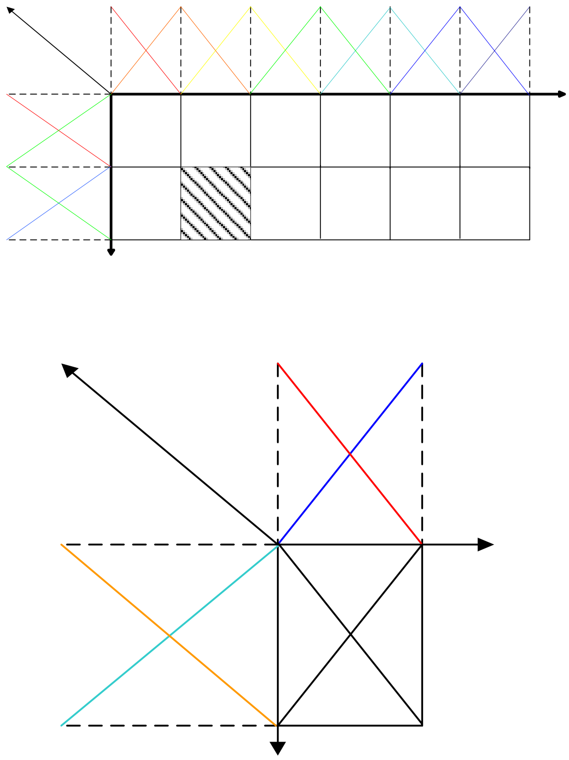

Figure 1 – 4 different areas in each interval

Since we were able to redesign the GenChess Fuzzy Rule Bases to include at most 2 inputs (2.2), we could adapt them to use 2-input TPE systems and obtain a faster evaluation function process. This process involved the adaptation and normalization of all fuzzy variables to comply with a TPE system. Figure 2 and Figure 3 show the membership functions, linguistic terms and normalized values we used (*Very Very Bad*, *Very Bad*, *Bad*, *Regular*, *Good*, *Very Good and Excellent*). Every parameter (input value) referred with a crisp value within the range [-50,50] is fuzzified accordingly.

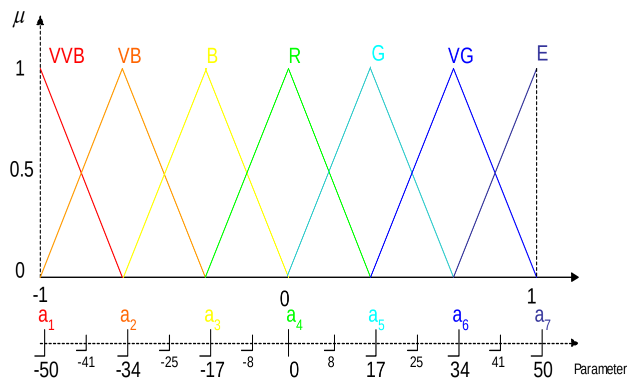

Figure 2–TPE linguistic terms and parameter normalization

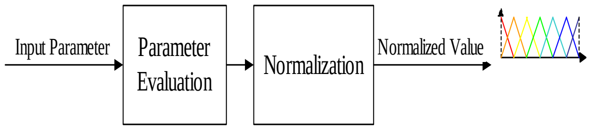

Figure 3–TPE input normalization

2.2 Fuzzy Implementation of Chess Tactics

Since it is not possible to present the complete Fuzzy GenChess model in a short paper, we will start with a general overview and then focus on a few selected details that can show Fuzzy GenChess implementation's philosophy.

The approach we used to implement the chess expert tactics consists in using the modelled knowledge to compute an evaluation function of the chessboard for each play. Each piece of the board is evaluated using fuzzy rule bases that were built using expert knowledge. Different parameters were considered in the evaluation depending on the piece type.

A certain fuzzy linguistic value is then computed to each piece. For example, the Bishop's value is computed according to its position on the board, its mobility and the dependence on the other bishop. In the end that bishop can be classified as a Very Very Bad, Very Bad, Bad, Regular, Good , Very Good or Excellent Bishop.

After all pieces are evaluated, their qualitative value is defuzzified according to their category. For instance, a Rook's value can range from around 360 (when standing without mobility, in an innocuous position, without any interaction with the Queen) to almost 700 (with an almost empty board, interacting with the Queen and able to directly attack the opponent's King), while a Bishop will end up with a value ranging from 200 to 430.

The value of a given play is based on the evaluation of all pieces and on additional fuzzy tactic bonus and penalizations that cannot be solely based on individual piece evaluation.

One must note that no search enhancing/accelerating methods – like quiescence search, search extensions, intelligent pruning or transposition tables – are used (although they are entirely compatible with our approach). This way we are able to guarantee that the single performance distinguishing factor between different approaches is the evaluation function.

Table 2 shows which input parameters were considered most relevant by the experts to evaluate each different chess piece. Each of these parameters can have a fixed value (e.g., the value of each board position for a Knight), or variable value (e.g.1, the value of each board position for the King, which changes as the games evolves; e.g.2, the mobility of the Rook, that is dependent on having its path blocked by other pieces). Most parameters are fuzzified and normalized according to 2.1, but a few ones ("Pair of Bishops", and some Pawn parameters) are crisp and, therefore, are used on differently (2.2.2).

In order to use 2-input TPE systems, the evaluation of pieces that need more than 2 input parameters had to be restructured. This was done considering expert's opinion regarding the dependence or independence between the input parameters for each piece.

Table 2– Inputs for Fuzzy Piece Evaluation

Piece	Inputs
King	Threat (based on the number of adjacent board positions under attack) Protection Position (position evaluation changes during game)
Queen	Currently none – has a permanent very high evaluation
Rook	Position (until end of midgame) Mobility (column + line) Queen Interaction
Bishop	Position Mobility Pair of Bishops
Knight	Position
Pawn	Position Promotion Proximity Passed Isolated Doubled Protected

2.2.1 *King's Evaluation*

Figure 4 shows how the 3 parameters used for King evaluation are structured in the inference process.

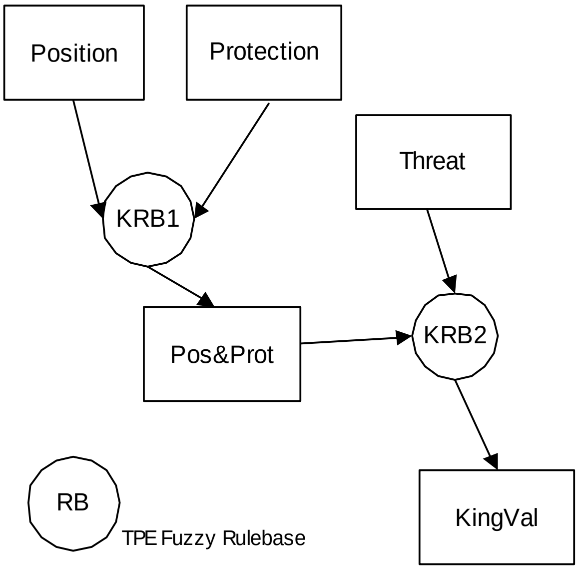

Figure 4–Fuzzy evaluation (King)

Each TPE Fuzzy Rule base in Figure 4 can be represented by a table. Table 3 shows KRB2, the fuzzy rule base that infers the King value using parameters “Threat” and “Position&Protection”.

Table 3 – KRB2: King Rule base 2

		Threat						
	KingVal	*VVB*	*VB*	B	*R*	*G*	*VG*	*E*
Pos&Prot	*VVB*	*VVB*	*VB*	*VB*	*VB*	*VB*	*VB*	*VB*
	VB	*VVB*	*VB*	*VB*	*VB*	*B*	*B*	*B*
	B	*VVB*	*VB*	*VB*	*B*	*R*	*R*	*R*
	R	*VVB*	*VB*	*VB*	*R*	*G*	*G*	*G*
	G	*VVB*	*VB*	*VB*	*R*	*G*	*VG*	*VG*
	VG	*VVB*	*VB*	*VB*	*VG*	*VG*	*VG*	*E*
	E	*VVB*	*VB*	*VB*	*VG*	*VG*	*E*	*E*

The “Threat” parameter can be used as a simple example of how expert knowledge was adapted and fuzzified:

1 - “Threat” accounts for the number of King adjacent board positions that are under direct attack by enemy pieces (#threats);

2 - Experts expressed linguistically how good or bad is the “Threat” according to #threats;

3 – Expert opinions were normalized in order to be used in the TPE system (Table 4).

Table 4 – Modeling and normalization of King’s threat

#threats	0	1	2	3	4	5	6	7	8
Threat	20	12	0	-16	-32	-48	-50	-50	-50

The other Fuzzy TPE Rule Base, KRB1 involves the King position in the chessboard, and how well is the King protected behind a Pawn structure.

Note that there are factors considered while evaluating the King that are not represented in Figure 4, namely the fact that the position evaluation changes according to the game phase. Figure 6 and Figure 7 show how is the King’s “Board Position” parameter evaluated during different game phases. Figure 5 shows the King evaluation’s linguistic terms. Note that these terms do not need to comply with TPE’s membership function restrictions.

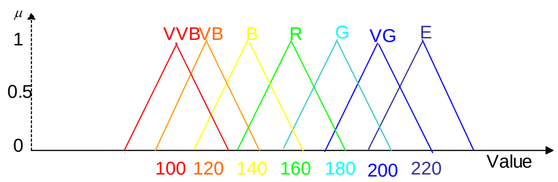

Figure 5– King Value linguistic terms

0	0	-4	-10	-10	-4	0	0
-4	-4	-8	-12	-12	-8	-4	-4
-12	-16	-20	-20	-20	-20	-16	-12
-16	-20	-24	-24	-24	-24	-20	-16
-16	-20	-24	-24	-24	-24	-20	-16
-12	-16	-20	-20	-20	-20	-16	-12
-4	-4	-8	-12	-12	-8	-4	-4
0	0	-4	-10	-10	-4	0	0

Figure 6 – King’s board position evaluation until midgame

0	6	12	18	18	12	6	0
6	12	18	24	24	18	12	6
12	18	24	30	30	24	18	12
18	24	30	36	36	30	24	18
18	24	30	36	36	30	24	18
12	18	24	30	30	24	18	12
6	12	18	24	24	18	12	6
0	6	12	18	18	12	6	0

Figure 7 – Endgame King’s board position evaluation

2.2.2 *Pawn’s Evaluation*

The Pawn is probably one of the most important pieces in chess, and often the deciding factor. This is mainly due to the fact that the Pawn can be promoted when reaches the opposite side of the board. Therefore a Pawn should be stimulated to advance in the board. This stimulus can be easily modelled by giving a better evaluation to forward board positions. Figure 8 shows Pawn board “Position” parameter.

However, Pawn advance must be properly supported, or the Pawn will become an easy target. To provide this support, the Pawn is the piece that has more parameters (six) in its evaluation. Since most of these parameters are crisp, there is no need to fuzzify each of them. Table 5 shows how the Fuzzy GenChess model combines 5 Pawn evaluation parameters to obtain a fuzzy parameter concerning “Pawn Advance Support”.

12	16	24	32	32	24	16	12
12	16	24	32	32	24	16	12
8	12	16	24	24	16	12	8
6	8	12	16	16	12	8	6
6	8	8	10	10	8	8	6
4	4	4	0	0	4	4	4
0	0	0	0	0	0	0	0

Figure 8 - Pawn board position evaluation

Table 5 – Pawn Advance Support evaluation

Promotion Proximity	Passed	Isolated	Doubled	Protected	Support
Excellent	x	x	x	x	VG
Good	Yes	x	x	x	0,5 G ; 0,5 VG
Good	No	x	x	Yes	0,5 G ; 0,5 VG
Good	No	x	x	No	VB
Far	x	No	No	No	R
Far	x	No	No	Yes	G
Far	x	No	No	Double	0,5 G ; 0,5 VG
Far	x	Yes	No	x	B
Far	X	Yes	Yes	x	VB
Far	X	No	Yes	Yes	0,5 B ; 0,5 R
Far	X	No	Yes	No	0,5 R ; 0,5 G
Far	X	No	Yes	Double	G

The final evaluation of each Pawn is obtained by the inference of a Fuzzy TPE Rule Base involving the parameters "Position" and "Pawn Advance Support". Table 6 shows the Pawn TPE Rule base. Note that some rules are not defined since they will never occur.

Figure 9 shows the Pawn evaluation's linguistic terms.

Table 6 - Pawn Rule base

		Pawn Advance Support						
	PawnVal	*VVB*	*VB*	B	*R*	*G*	*VG*	*E*
Position	*VVB*							
	VB							
	B							
	R		*VVB*	*VB*	*B*	*R*	*G*	
	G		*VB*	*B*	*R*	*G*	*VG*	
	VG		*B*	*R*	*G*	*VG*	*E*	
	E							

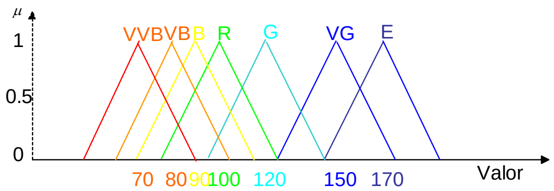

Figure 9– Pawn Value linguistic terms

2.2.3 Knight, Bishop and Rook's Evaluation

The remnant pieces are evaluated depending on their parameter's number and type. The Knight's evaluation is simply based on the piece board position. The Bishop and the Rook use a multi level Fuzzy TPE Rule base structure similar to the one used to evaluate the King.

Figure 10, Figure 11, and Figure 12 shows the evaluation linguistic terms for the Rook, Bishop and Knight.

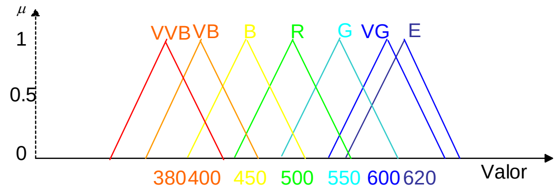

Figure 10– Rook Value linguistic terms

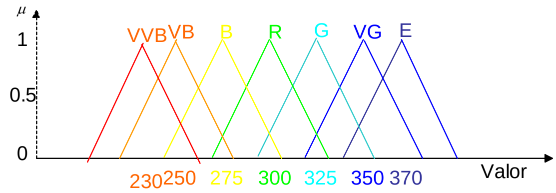

Figure 11– Bishop Value linguistic terms

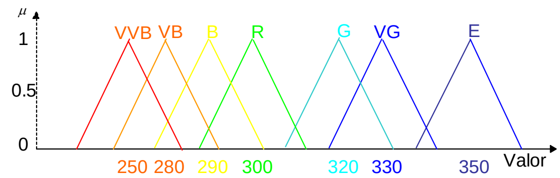

Figure 12– Knight Value linguistic terms

3 Results

The GenChess Fuzzy system was tested in simulated computer tournaments against opponents using several types of board evaluation functions. These included opponents using:

- Alpha-beta search with traditional chessboard evaluation functions based on piece weight (the rook is worth 5 pawns, the knight 3 pawns, etc);
- Alpha-beta search with an evaluation function trained by an evolutionary algorithm;
- The Simple Chess Program [5] (which includes mechanisms to evaluate the board based on piece position, number of pieces, piece structure, etc.);

The tournaments also mixed opponents with different number of search plies of depth. This was used to obtain a measure for the computing time trade-off between using a more intelligent evaluation function vs. searching deeper.

The results show that the GenChess Fuzzy evaluation function is the best solution, since for a similar number of plies, and without any time limit, it wins tournaments on a consistent basis.

However, even with the extensive use of TPE's, as long as there is a time limit, the results change (the Simple Chess Program becomes the best approach), since in order to avoid loosing by time limit, the Fuzzy Chess approach must consistently stop its search at least one ply sooner than the other approaches, which is enough to deny its evaluation function advantages. An initial analysis shows that the most penalizing time consuming factor in the Fuzzy Chess approach is Pawn evaluation, not in the aspects related with the fuzzy inference, but in the algorithms that are used to compute the several crisp parameters used in the fuzzy computation (which involve bitboard manipulation [2][3][4]). By improving those algorithms, one can still hope for some improvement in what regards computing time efficiency. Our target would obviously be to reduce the one ply deficit. However, one must note that one cannot simply eliminate the complex Pawn evaluation, since tests show that Pawn evaluation is one of the decisive winning factors over the Simple Chess approach.

Unfortunately, most good chess computer packages' performance is not based on its evaluation function (which is usually rather similar to the Simple Chess one), but on search enhancing techniques and programming efficiency that allows deeper and more efficient ply search. Therefore it was not possible to directly compare our Fuzzy Chess approach with those programs. It is however possible to conclude that GenChess Fuzzy Chess Tactics can provide a better evaluation of the board, but that the necessary extra computation time is a trade-off that must be seriously considered when a game has a time limit.

Another issue related with Fuzzy GenChess is the end game phase performance. Close to 40% of the games where both players use Fuzzy Chess tactics end up in a draw due to move repetition during the end game phase. Therefore, one should develop special heuristics to deal with this aspect of the game.

4 Conclusions and Future Developments

There is no doubt that the use of a Fuzzy approach to model the tactics of the game of chess can provide good results, and could be of interesting use in games where time limit is not an issue (like mail tournaments). However, even with the use of fuzzy TPE systems, and even if we can further improve computing time performance, the main problem in using fuzzy knowledge representation in the game of chess, lie in the fact that one will probably always have a slower, even if better, evaluation function. The extra needed computing power could probably always be used to perform deeper searches, which could lead to finding a better play.

Our current model is still not final. There is still a lot of work to do in what concerns rule, linguistic terms and parameter optimization (while playing against GenChess, one can still observe some non-optimal decisions that can be traced to poor rule implementation). Future planned developments include fuzzy parameter optimization using a fuzzy evolutionary algorithm approach.

Other developments include taking advantage of TPE's property that allows the increase in the number of linguistic terms (granularity) without relevant computing time penalty.

5 References

[1] Arena Chess GUI: http://www.playwitharena.com/

[2] Chess Programming Theory: http://www.chessbrain.net/beowulf/theory.html

[3] Computer Chess Programming: http://www.xs4all.nl/~verhelst/chess/programming.html

[4] GameDev – Chess Programming: http://www.gamedev.net/reference/programming/features/chess1

[5] GNUChess http://www.gnu.org/software/chess/chess.html

[6] Silva, P.J.R., "GenChess – Xadrez Inteligente", Graduation Thesis, 26/2003, DEEC IST-UTL, Lisboa, Portugal, Jul. 2004.

[7] Sudkamp,T., Hammell,R.J., "Interpolation, Completion, and Learning Fuzzy Rules", IEEE Transactions on Systems, Man, and Cybernetics, Vol. 24, 2, 1994

[8] Yan, D.C., "GenChess II – Xadrez Inteligente", Graduation Thesis, DEEC IST-UTL, Lisboa, Portugal, Jul. 2005