Complex Problem Solving With Neural Networks: Learning Chess

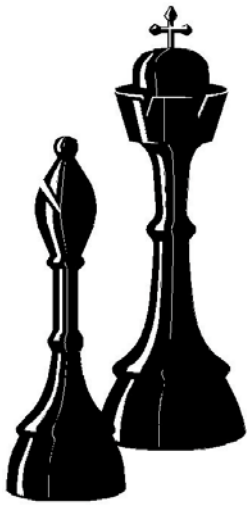
Mr. Jack Sigan

Dr. Aleksander Malinowski, Advisor

Dept. of Electrical and Computer Engineering

BRADLEY UNIVERSITY

December 2, 2004



Outline

- Neural network introduction
- Chess and neural networks
- Applicable standards and important research
- Chess-specific network architectures
  - Geographical approach
  - Functional approach
- Data representations and input vectors
  - Possible modifications to coding
- Timeline
- Parts and materials

Neural Networks

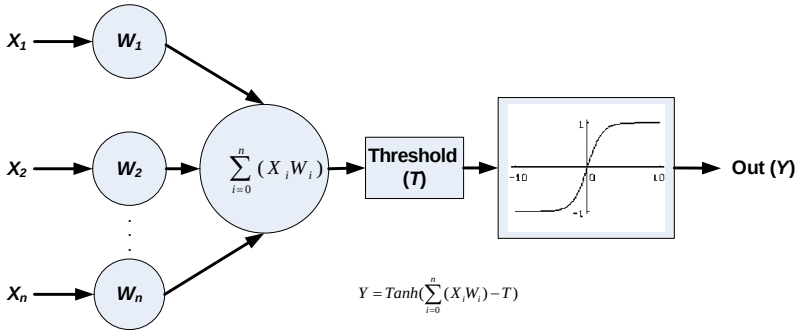


Figure 1A: Node structure with hyperbolic tangent activation function

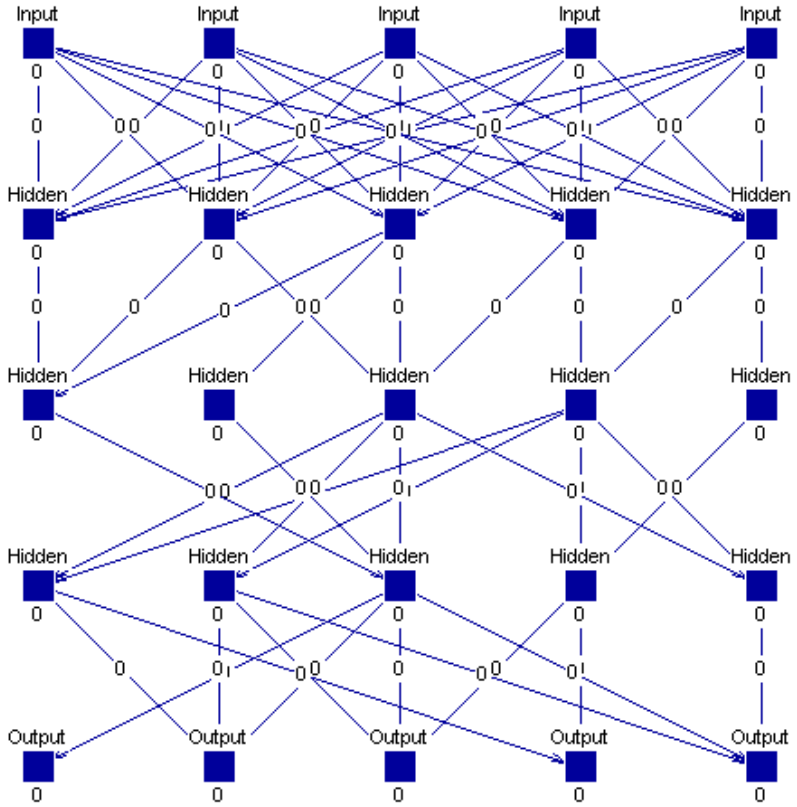


Figure 1B: Simple partially connected neural network structure from Stuttgart Neural Network Simulator (SNNS)

Neural Networks

- May be required to use radial basis function networks
  - Excellent at pattern classification
  - Rapid training time
  - Single hidden layer in network
  - Determines “distance” between input vector and weight vector

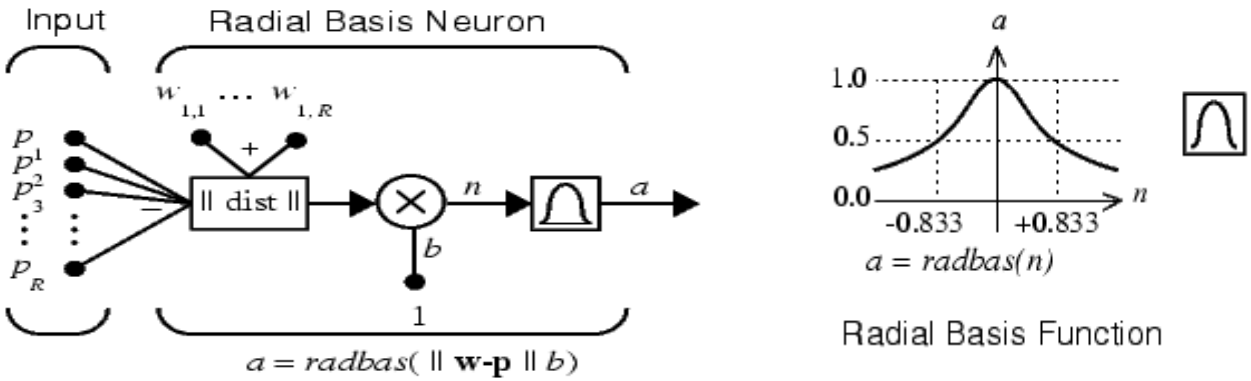


Figure 2: Radial basis node model with Gaussian distribution function

Chess and Neural Networks?

- Demonstrates complex decision making
- Highly nonlinear problem
- Schemas
- Widely studied
- Massive amounts of available data
- Success with checkers
- Mixed results with chess in the past

Standards and research

- Numerous applicable “standards”
  - Chess “laws”
    - FIDE (*Fédération Internationale des Échecs*)
    - http://www.fide.com
  - PGN file standard
    - rec.games.chess, 1994
  - EPD file standard
    - Format supplied by “EPD_Position.exe” (standard?)
- Most influential research
  - K. Chellapilla and D.B. Fogel
  - C. Posthoff, S. Schawelski and M. Schlosser

Parallel Network Designs

- Decrease learning cycle time
- Less destructive learning process
- Multiple “suggested” moves may be returned
- Simpler network architectures
- 2 paradigms for deconstructing chess
  - Geographical “move based”
  - Functional “piece based”
- External logic is applied to both paradigms to filter out illegal moves or impossible moves

Parallel Network Designs

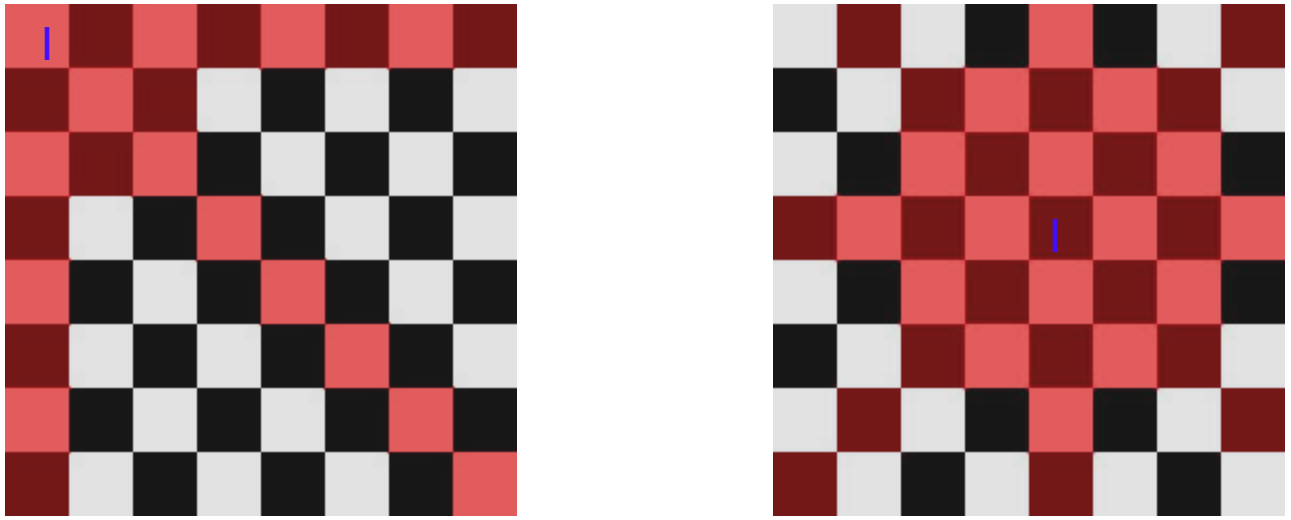


Figure 3: Mapping the legal moves in chess, using overlay consisting of queen + knight moves

Excluding castling, there are 1856 moves possible —ignoring the piece type which is moved

Example: Moving from d3 to d4 is considered ONE possible move, whether the piece is a pawn, queen, king, etc.

Approach A: Geographical

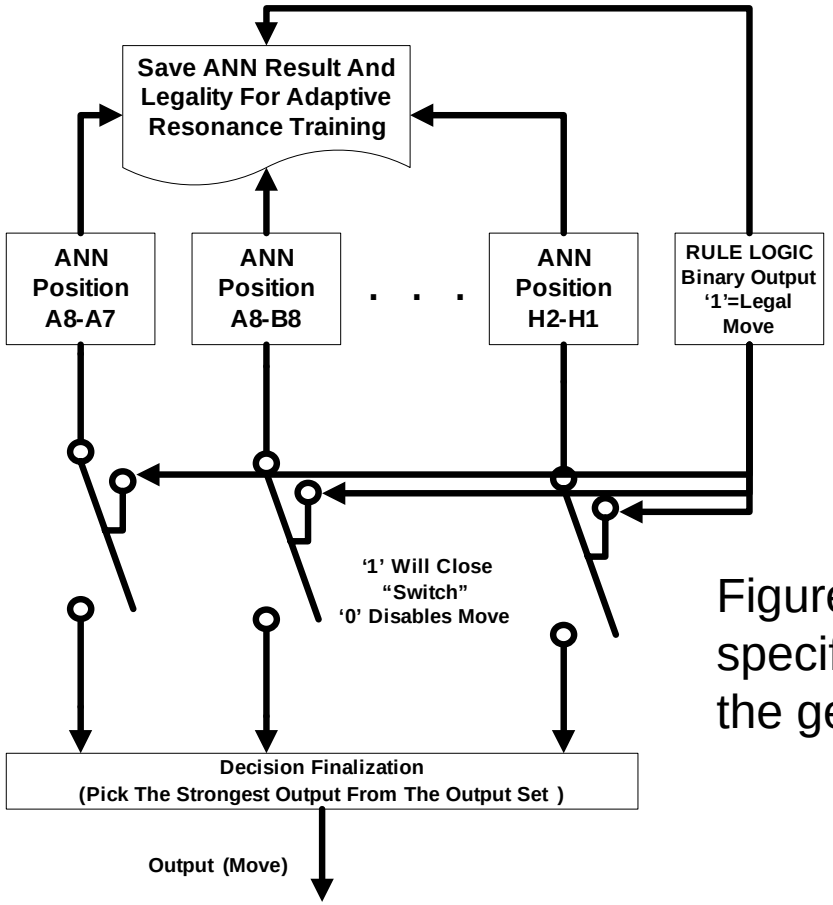


Figure 4: Design with "move specific" neural networks—the geographical approach

Approach B: Functional

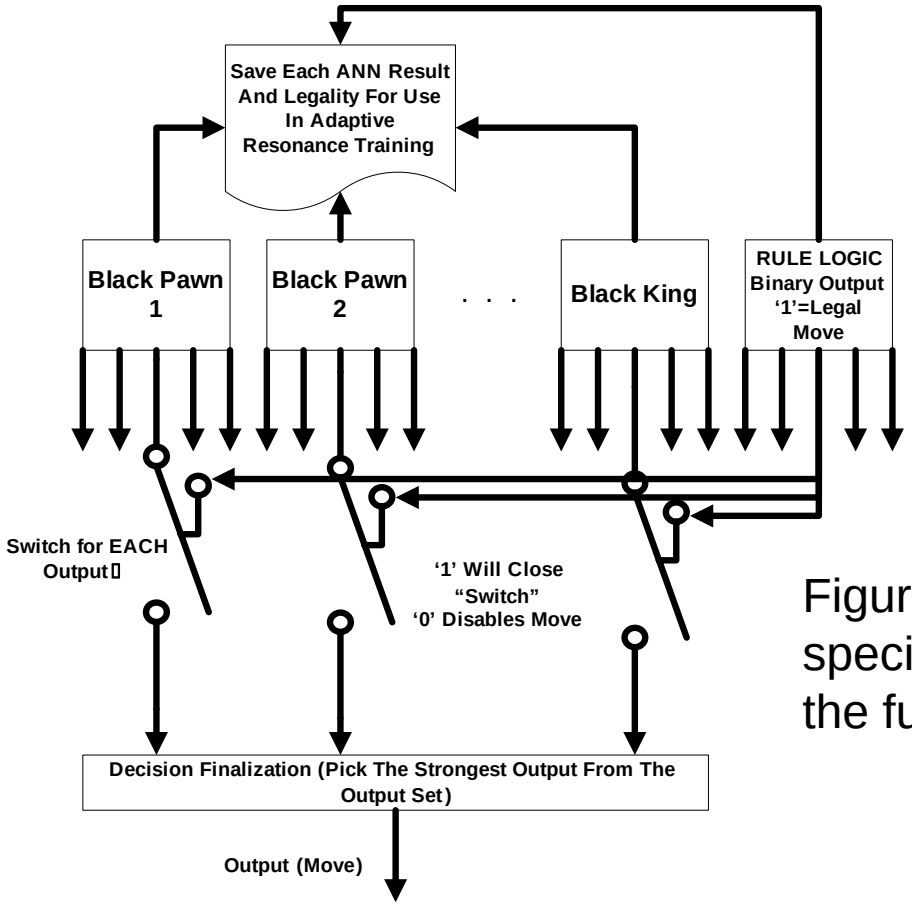


Figure 5: Design with "piece specific" neural networks—the functional approach

Data Representations

```
 1. e4 d6      2. d4 Nf6  3. Nc3 g6    4. Nf3 Bg7    5. Be2 O-O    6. O-O Bg4
 7. Be3 Nc6    8. Qd2 e5  9. d5 Ne7    10. Rad1 Bd7  11. Ne1 Ng4   12. Bxg4 Bxg4
13. f3 Bd7    14. f4Bg4  15. Rb1 c6    16. fxe5 dxe5 17. Bc5 cxd5  18. Qg5 dxe4
19. Bxe7 Qd4+ 20. Kh1f5  21. Bxf8 Rxf8 22. h3 Bf6    23. Qh6 Bh5   24. Rxf5 gxf5
25. Qxh5 Qf2  26. Rd1e3  27. Nd5 Bd8   28. Nd3 Qg3   29. Qf3 Qxf3  30. gxf3 e4
31. Rg1+ Kh8  32. fxe4 fxe4 33. N3f4 Bh4 34. Rg4 Bf2 35. Kg2 Rf5   36. Ne7 1-0
```

Figure 6: Example of the PGN (algebraic) standard

```
rnbqkbnr/pppppppp/8/8/8/8/PPPPPPPP/RNBQKBNR w KQkq - pm d4;
rnbqkbnr/pppppppp/8/8/3P4/8/PPP1PPPP/RNBQKBNR b KQkq d3 pm Nf6;
rnbqkb1r/pppppppp/5n2/8/3P4/8/PPP1PPPP/RNBQKBNR w KQkq - pm Nf3;
rnbqkb1r/pppppppp/5n2/8/3P4/5N2/PPP1PPPP/RNBQKB1R b KQkq - pm b6;
```

Figure 7: Example of the EPD (string) format

Preprocessing

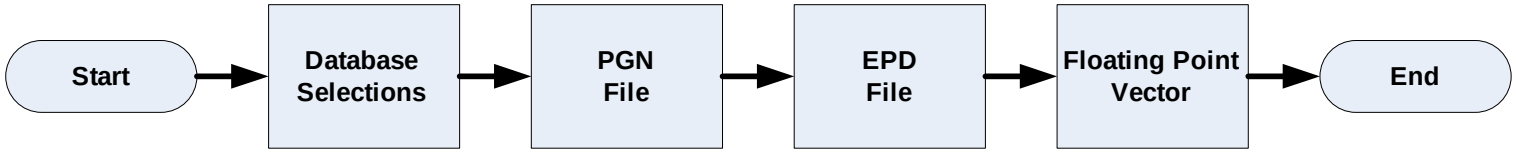


Figure 8: The game data preprocessing procedure

•Board positional data, plus a ‘yes’ or ‘no’ decision in regards to making the specific move must be in the floating point vector.

•A 50/50 mix of ‘yes’ and ‘no’ samples will be used in all training sets

•The geographical approach does not differentiate between pieces to be moved, only the initial and final positions are important

Input Vector Creation

Piece	EPD Character Black, white	Weight Black, white
King	k,K	1.0, -1.0
Queen	q,Q	0.9, -0.9
Rook	r,R	0.5, -0.5
Knight	n,N	0.4, -0.4
Bishop	b.B	0.3, -0.3
Pawn	p,P	0.1, -0.1

Figure 9: “Standard” values for pieces used in the floating point input vector creation

```
# Input pattern 1:
0.5 0.4 0.3 0.9 1 0.3 0.4 0.5
0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
-0.1 -0.1 -0.1 -0.1 -0.1 -0.1 -0.1 -0.1
-0.5 -0.4 -0.3 -0.9 -1 -0.3 -0.4 -0.5
# output pattern 1:
1
```

Figure 10: Floating point input vector for the initial board position

Training Vector Coding

- May need to evaluate other formats
  - Binary representation (used in end-game research)
  - Multiple spatial relationships?
- Training must be started to know!

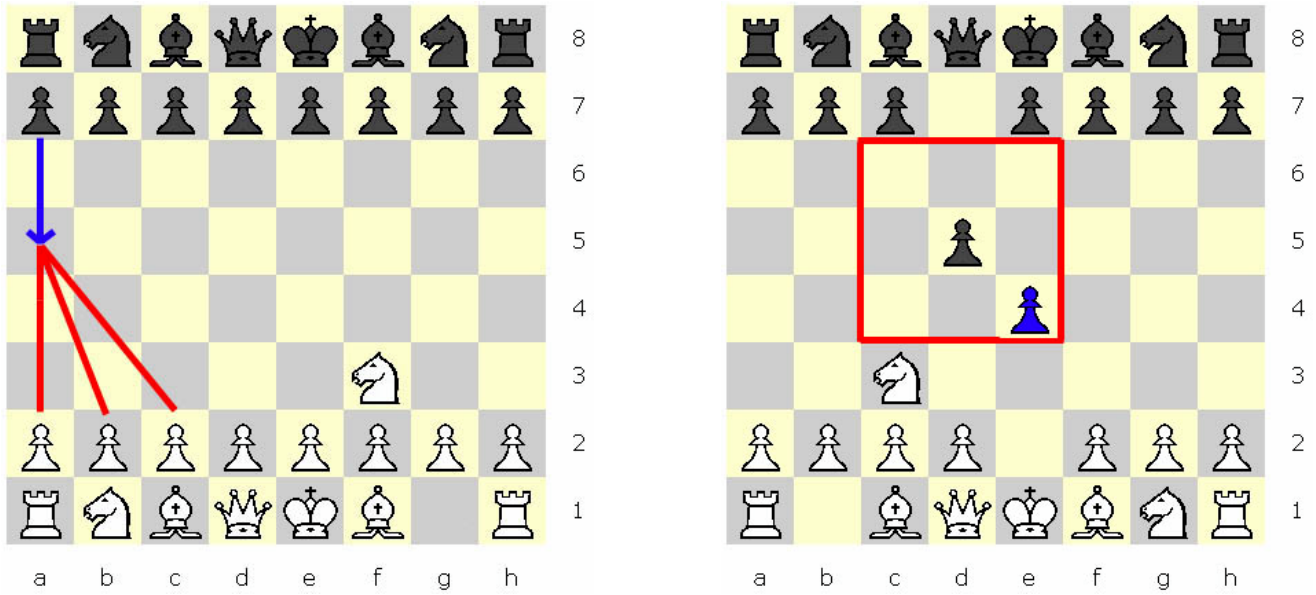


Figure 11: Possible spatial relationships

Timeline

Date	Goals and progress
May-04	Decide overall purpose of the project
Jun-04 to Jul-04	Work on neural network framework
Aug-04	Redefine project goals and choose to use SNNS instead of new framework
Sep-04	Data processing functions designed and Chessbase 9.0 identified as database
21 Oct-04	Network generator program is created and data processing defined further
28 Oct-04	Order ChessBase 9.0 and evaluate training speeds
4 Nov-04	Argonne presentation and ChessBase 9.0 arrives, begin data extraction.
11 Nov-04	Extract Data, begin investigating possible network sizes and connectionisms
18 Nov-04	Extract Data, begin investigating radial basis function networks.
25 Nov-04	Extract Data, work on proposal

Timeline

2 Dec-04	**Extract Data, proposal presentation**
9 - 16 Dec-04	**Extract Data and begin to look at feed forward and radial basis comparison**
23 Dec-04	**Extract Data and work on rule logic and ANN integration module**
30 Dec-04	**Process Data (PGN to EPD), journal paper?**
6 Jan-04	**Process Data (EPD to FP), create and initialize all networks, journal paper?**
13 Jan-04	**Design a process for training and test on 4 or 5 machines, journal Paper?**
20 Jan to 24 March-04	**Train on maximum number of PCs, evaluate performance/make changes**
31 Mar-04	**Integrate remaining modules (final interface), test against human players**
7 Apr-04	**Continue testing system, evaluate rating if possible**
14 – 28 Apr-04	**Begin preparing for final presentations and expo + finish loose ends**

Parts and Materials

- ChessBase 9.0 Database: $389.00
- DVDRs
  - Roughly 20 will be needed to backup data: $20.00
- 160 GB external hard disk
  - For local data storage: $150.00
  - Personally purchased
- CPU Time
  - Off-hour access to laboratories will be required for training on as many PCs as possible
  - A full estimate of requirements will be made shortly

Questions?

Additional questions and comments are invited. Please contact:
Jack Sigan, jsigan@bradley.edu

Abstract

Chess has long been one of the most scrutinized, perplexing, and purely logical pursuits of man. Kasparov's defeat at the "hands" of Deep Blue indicates that computers, within a miniscule sixty years of evolution, can outperform the zenith of biological evolution in its crowning achievement of logical decision making.

Yet, not a single machine plays chess in the same manner as man, being capable of little more than brute force attacks on the game. Through experimentation with artificial neural networks with various topologies and learning algorithms, it is hypothesized that learning can be based on "schemas" found in recorded games.

Parallel Network Designs

- starting position *i*
- final position *f*
- $m_{if}=f(b_i)$ represents all legal moves for a board position b_i
- game *g* of *n* moves may be expressed as a set of board positions *bi, biЄg,* where *i* is the position number 0 to *n*.

$$L = \sum_{i=0}^{n} f(b_i)$$ Legal moves for a game of *n* positions

$$M = \sum_{i=0}^{\infty} (L_i)$$ Legal moves for chess (all games)

•In this design, it is required to create an individual ANN structure for all moves *t*, *tЄM. M*=1856, ignoring castling

Parallel Network Designs

- starting position *i*
- final position *f*
- piece *p*
- $m_{if}=f(p,b_i)$ represents all legal moves for a piece in b_i
- game *g* of *n* moves may be expressed as a set of board positions *bi, biЄg,* where *i* is the move number 0 to *n*.

$$L = \sum_{i=0}^{n} f(p, b_i)$$ Legal moves for a game of *n* moves

$$M = \sum_{i=0}^{\infty} (L_i)$$ Legal moves for a piece (all games)

- In this design, it is required to create an individual ANN structure for all pieces *p*, *p*=1 to 16

References

- [1] K. Chellapilla and D.B. Fogel. “Evolution, Neural Networks, Games and Intelligence.” *Proceedings of the IEEE*, vol. 87, no. 9, pp. 1471-1496, Sept. 1999.
- [2] K. Chellapilla and D.B. Fogel. "Anaconda Defeats Hoyle 6-0: A Case Study Competing an Evolved Checkers Program Against Commercially Available Software,” in *Proceedings of the 2000 Congress on Evolutionary Computation*, 2000, vol. 2, pp. 857-863.
- [3] C. Posthoff, S. Schawelski and M. Schlosser. “Neural Network Learning In a Chess Endgame,” in *IEEE World Congress on Computational Intelligence*, 1994, vol. 5, pp. 3420-3425.
- [4] R. Seliger. “The Distributed Chess Project.” Internet: http://neural-chess.netfirms.com/HTML/project.html, 2003 [Aug. 26, 2004].
- [5] University of Tübingen. “Stuttgart Neural Network Simulator.” Internet: http://www-ra.informatik.uni-tuebingen.de/software/JavaNNS/welcome_e.html, 2003 [Aug 30, 2004].
- [6] M. Chester. *Neural Networks*. Englewood Cliffs, NJ: PTR Prentice Hall, 1993, pp. 71-81.