

Neuroevolution

- These are selected (by Yoonsuck Choe) slides from Risto Miikkulainen's tutorial at the GECCO 2005 conference

1

Evolving Neural Networks

Risto Miikkulainen

Department of Computer Sciences

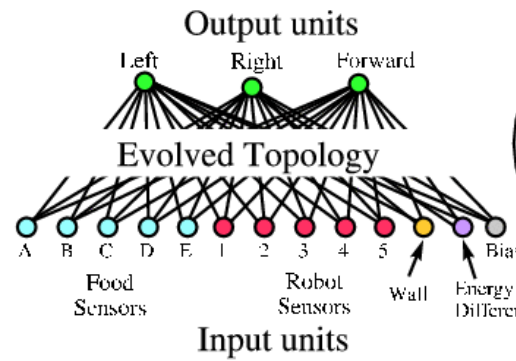
The University of Texas at Austin

<http://www.cs.utexas.edu/users/risto>

2

Neuroevolution Decision Strategies

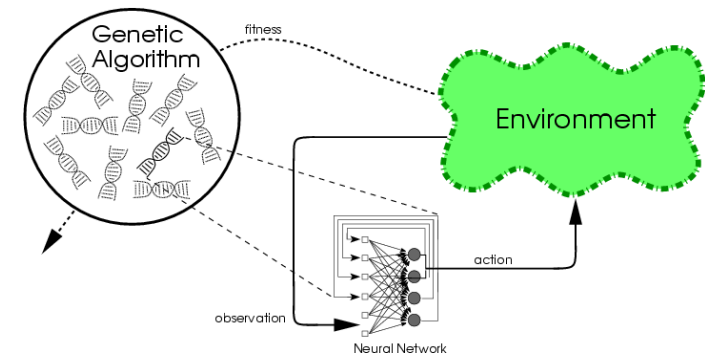
- Input variables describe the state
- Output variables describe actions
- Network between input and output
 - Hidden nodes
 - Weighted connections



- Execution:
 - Numerical activation of input
 - Nonlinear weighted sums
- Performs a nonlinear mapping
 - Memory in recurrent connections
- Connection weights and structure evolved

3

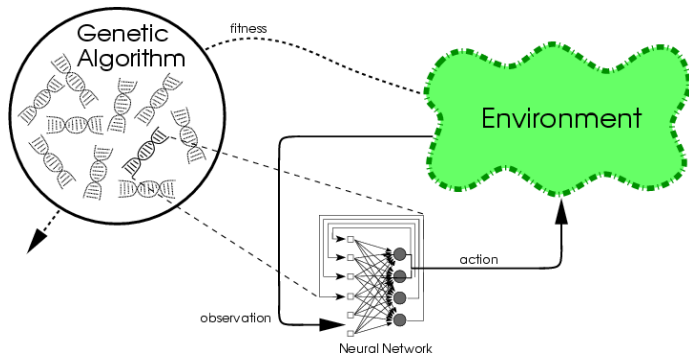
Conventional Neuroevolution (CNE)



- Evolving connection weights in a population of networks ^{19,38,39}
- Chromosomes are strings of weights (bits or real)
 - E.g. 10010110101100101111001
 - Usually fully connected, fixed topology
 - Initially random

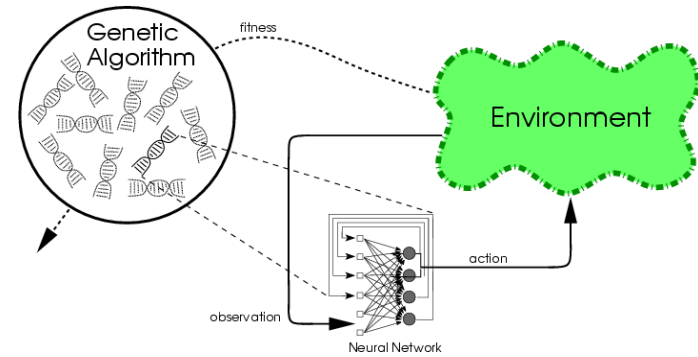
4

Conventional Neuroevolution (2)



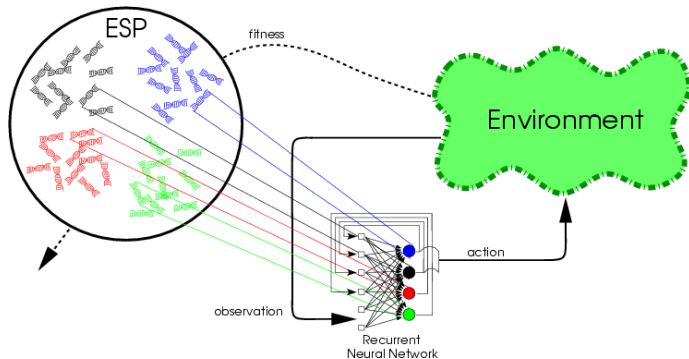
- Each NN evaluated in the task
 - Good NN reproduce through crossover, mutation
 - Bad thrown away
 - Over time, NNs evolve that solve the task
- Natural mapping between genotype and phenotype
- GA and NN are a good match!₅

Problems with CNE



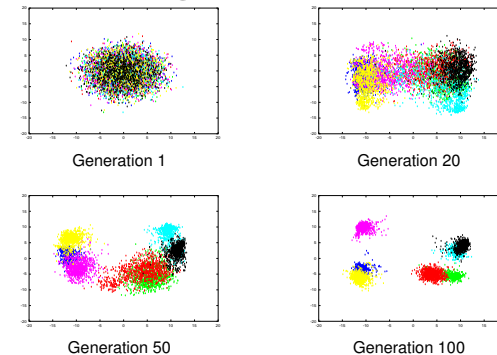
- Evolution converges the population (as usual with EAs)
 - Diversity is lost; progress stagnates
- Competing conventions
 - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
 - Thousands of weight values₅ at once

Advanced NE 1: Evolving Neurons



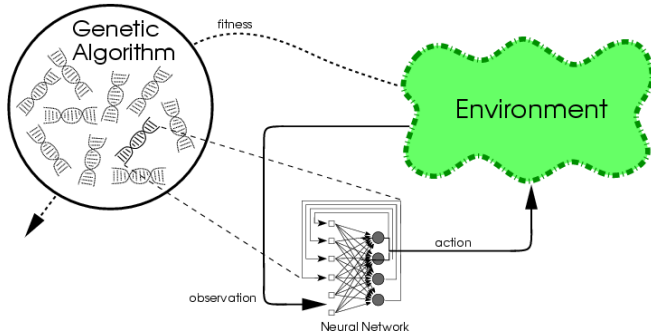
- Evolving individual neurons to cooperate in networks^{1,22,24} (Agogino GECCO'05)
- E.g. Enforced Sub-Populations (ESP²)
 - Each (hidden) neuron in a separate subpopulation
 - Fully connected; weights of each neuron evolved
 - Populations learn compatible subtasks

Evolving Neurons with ESP



- Evolution encourages diversity automatically
 - Good networks require different kinds of neurons
- Evolution discourages competing conventions
 - Neurons optimized for compatible roles
- Large search space divided into subtasks
 - Optimize compatible neurons

Advanced NE 2: Evolutionary Strategies

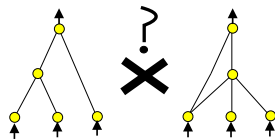


- Evolving complete networks with ES (CMA-ES¹⁵)
- Small populations, no crossover
- Instead, intelligent mutations
 - Adapt covariance matrix of mutation distribution
 - Take into account correlations between weights
- Smaller space, less convergence, fewer conventions

9

How Can Crossover be Implemented?

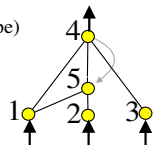
- Problem: Structures do not match



- Solution: Utilize historical markings

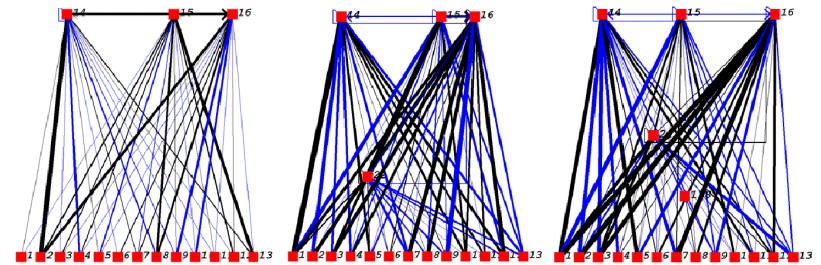
Genome (Genotype)						
Node	Node 1	Node 2	Node 3	Node 4	Node 5	
Genes	Sensor	Sensor	Sensor	Output	Hidden	
Connect	In 1	In 2	In 3	In 2	In 5	In 1
Genes	Out 4	Out 4	Out 4	Out 5	Out 4	Out 5
	Weight 0.7	Weight-0.5	Weight 0.5	Weight 0.2	Weight 0.4	Weight 0.6
	Enabled	DISABLED	Enabled	Enabled	Enabled	Enabled
	Innov 1	Innov 2	Innov 3	Innov 4	Innov 5	Innov 6
						Innov 11

Network (Phenotype)



11

Advanced NE 3: Evolving Topologies

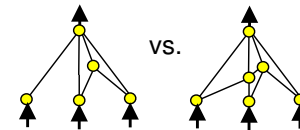


- Optimizing connection weights and network topology^{11,40}
- E.g. Neuroevolution of Augmenting Topologies (NEAT^{27,29})
- Based on *Complexification*
- Of networks:
 - Mutations to add nodes and connections
- Of behavior:
 - Elaborates on earlier behaviors

10

How can Innovation Survive?

- Problem: Innovations have initially low fitness

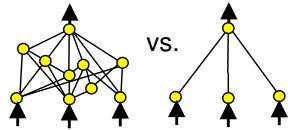


- Solution: Speciate the population
 - Innovations have time to optimize
 - Mitigates competing conventions
 - Promotes diversity

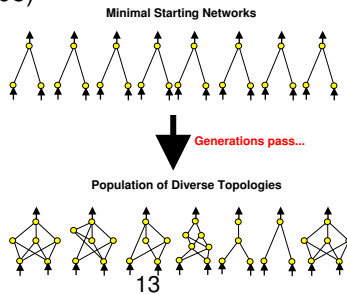
12

How Can We Search in Large Spaces?

- Need to optimize not just weights but also topologies



- Solution: Start with minimal structure and complexify
 - Hidden nodes, connections, input features³⁷(Whiteson GECCO'05)



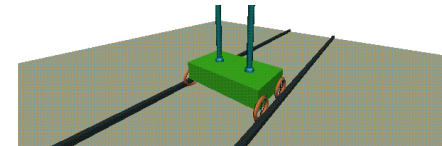
Extending NE to Applications

- Evolving composite decision makers³⁶
- Evolving teams of agents^{3,28,41}
- Utilizing coevolution³⁰
- Real-time neuroevolution²⁸
- Combining human knowledge with evolution⁸

Further NE Techniques

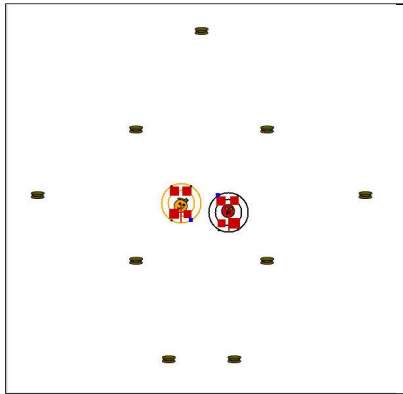
- Incremental evolution^{13,33,39}
- Utilizing population culture^{2,18}
- Evolving ensembles of NNs^{16,23,36}
(Pardoe GECCO'05)
- Evolving neural modules²⁵
- Evolving transfer functions and learning rules^{4,26?}
- Combining learning and evolution

Applications to Control



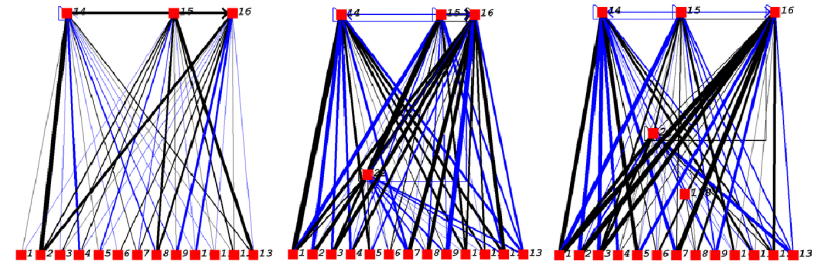
- Pole-balancing benchmark
 - Originates from the 1960s
 - Original 1-pole version too easy
 - Several extensions: acrobat, jointed, 2-pole, particle chasing²³
- Good surrogate for other control tasks
 - Vehicles and other physical devices
 - Process control³⁴

Competitive Coevolution



- Evolution requires an opponent to beat
- Such opponents are not always available
- Co-evolve two populations to outdo each other
- How to maintain an arms race?

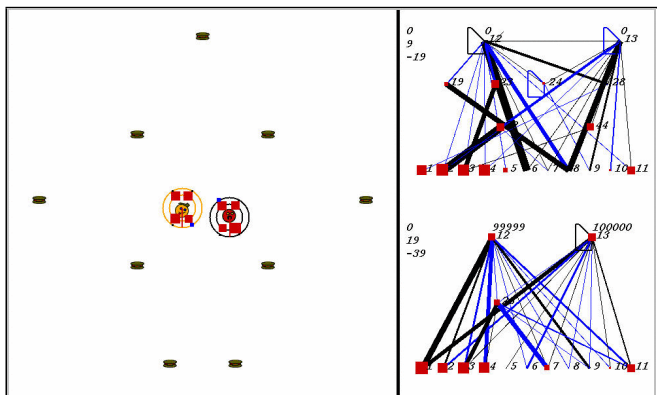
Competitive Coevolution with NEAT



- Complexification elaborates instead of alters
 - Adding more complexity to existing behaviors
- Can establish a coevolutionary arms race
 - Two populations continually outdo each other
 - Absolute progress, not just tricks

18

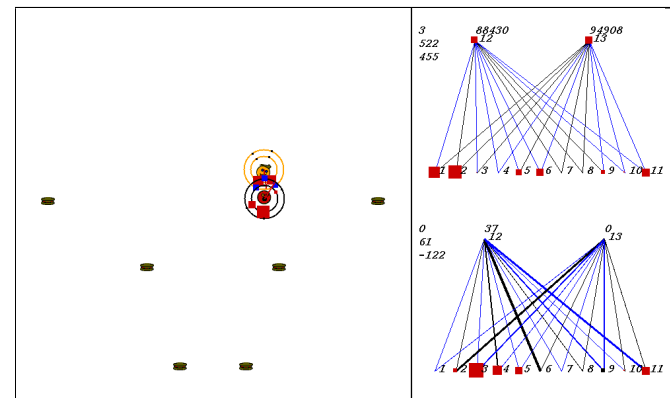
Robot Duel Domain



- Two Khepera-like robots forage, pursue, evade³⁰
 - Collect food to gain energy
 - Win by crashing to a weaker robot

19

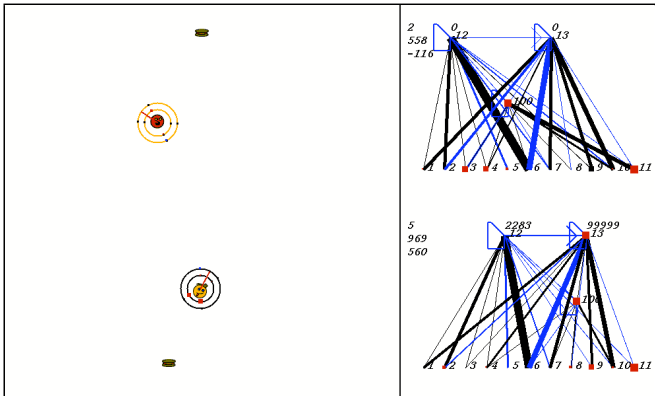
Early Strategies



- Crash when higher energy
- Collect food by accident
- DEMO

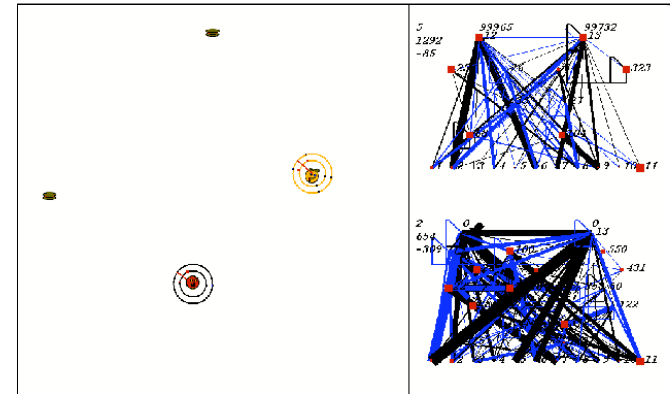
20

Mature Strategies



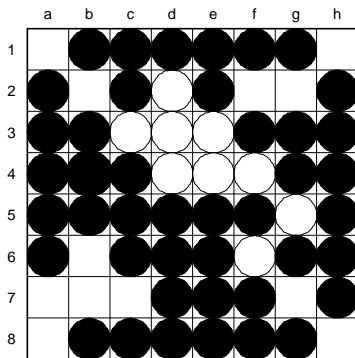
- Collect food to gain energy
- Avoid moving to lose energy
- Standoff: Difficult to predict outcome
- DEMO 21

Sophisticated Strategy



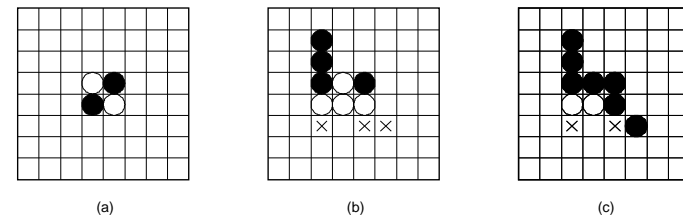
- “Fake” a move up, force away from last piece
- Win by making a dash to last piece
- Complexification → arms race
- DEMO 22

Applications to Games



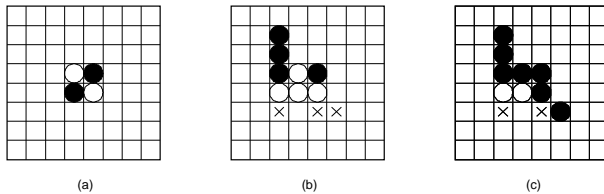
- Good research platform
 - Controlled domains, clear performance, safe
 - Economically important; training games possible
- Board games: beyond limits of search
 - Evaluation functions in checkers, chess^{5,9,10}
 - Filtering information in go, othello^{20,31}

Discovering Novel Strategies in Othello



- Players take turns placing pieces
- Each move must flank opponent's piece
- Surrounded pieces are flipped
- Player with most pieces wins

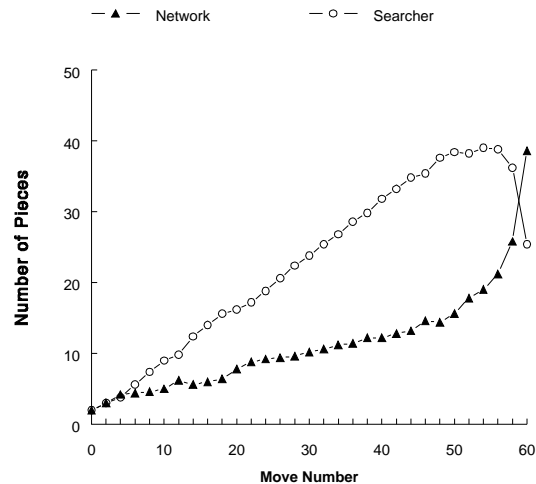
Strategies in Othello



- Positional
 - Number of pieces and their positions
 - Typical novice strategy
- Mobility
 - Number of available moves: force a bad move
 - Much more powerful, but counterintuitive
 - Discovered in 1970's in Japan

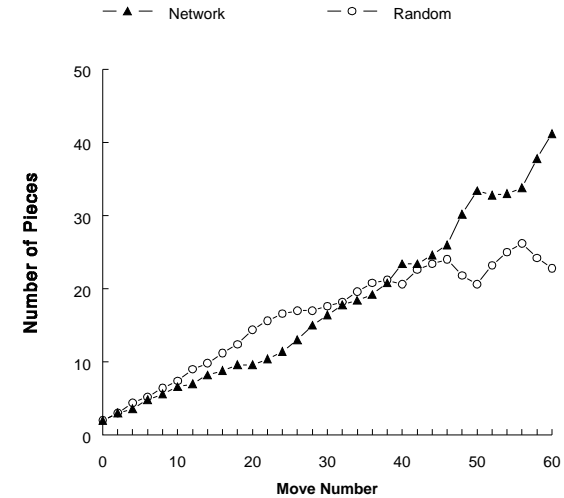
25

Evolving Against an α - β Program



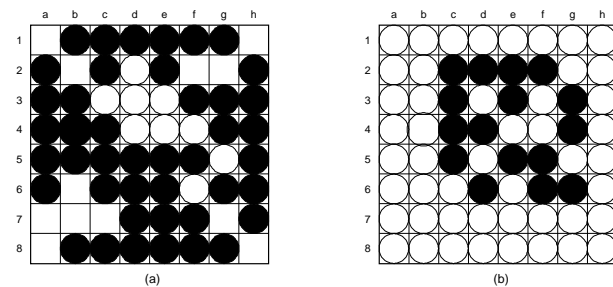
- Iago's positional strategy destroyed networks at first
- Evolution turned low piece count into an advantage
- Mobility strategy emerged!
- Achieved 70% winning percentage

Evolving Against a Random Player



- Network sees the board, suggests moves by ranking²¹
- Networks maximize piece counts throughout the game
- A positional strategy emerges
- Achieved 97% winning percentage

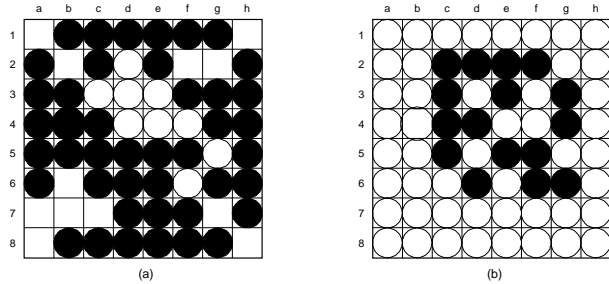
Example game



- Black's positions strong, but mobility weak
- White (the network) moves to f2
- Black's available moves b2, g2, and g7 each will surrender a corner
- The network wins by forcing a bad move

28

Discovering Novel Strategies



- Neuroevolution discovered a strategy novel to us
- “Evolution works by tinkering”
 - So does neuroevolution
 - Initial disadvantage turns into novel advantage

29

Numerous Other Applications

- Creating art, music⁶
- Theorem proving⁷
- Time-series prediction¹⁷
- Computer system optimization¹²
- Manufacturing optimization¹⁴
- Process control optimization^{34,35}
- Etc.

31

Future Challenge: Utilizing Knowledge



- Given a problem, NE discovers a solution by exploring
 - Sometimes you already know (roughly) what works
 - Sometimes random initial behavior is not acceptable
- How can domain knowledge be utilized?
 - By incorporating rules (Yong GECCO'05)
 - By learning from examples

Conclusion

- NE is a powerful technology for sequential decision tasks
 - Evolutionary computation and neural nets are a good match
 - Lends itself to many extensions
 - Powerful in applications
- Easy to adapt to applications
 - Control, robotics, optimization
 - Artificial life, biology
 - Gaming: entertainment, training
- Lots of future work opportunities
 - Theory not well developed
 - Indirect encodings
 - Learning and evolution
 - Knowledge and interaction

32

References

- [1] Adrian Agogino, Kagan Tumer, and Risto Miikkulainen. Efficient credit assignment through evaluation function decomposition. In *Proceedings of the Genetic and Evolutionary Computation Conference*, 2005.
- [2] Richard K. Belew. Evolution, learning and culture: Computational metaphors for adaptive algorithms. *Complex Systems*, 4:11–49, 1990.
- [3] Bobby D. Bryant and Risto Miikkulainen. Neuroevolution for adaptive teams. In *Proceedings of the 2003 Congress on Evolutionary Computation*, 2003.
- [4] David J. Chalmers. The evolution of learning: An experiment in genetic connectionism. In Touretzky et al. [32], pages 81–90.
- [5] Kumar Chellapilla and David B. Fogel. Evolution, neural networks, games, and intelligence. *Proceedings of the IEEE*, 87:1471–1496, 1999.
- [6] Chun-Chi Chen and Risto Miikkulainen. Creating melodies with evolving recurrent neural networks. In *Proceedings of the INNS-IEEE International Joint Conference on Neural Networks*, pages 2241–2246, Piscataway, NJ, 2001. IEEE.
- [7] Nirav S. Desai and Risto Miikkulainen. Neuro-evolution and natural deduction. In *Proceedings of The First IEEE Symposium on Combinations of Evolutionary Computation and Neural Networks*, pages 64–69, Piscataway, NJ, 2000. IEEE.
- [8] James Fan, Raymond Lau, and Risto Miikkulainen. Utilizing domain knowledge in neuroevolution. In *Machine Learning: Proceedings of the 20th Annual Conference*, 2003.
- [9] David B. Fogel. *Blondie24: Playing at the Edge of AI*. Kaufmann, San Francisco, 2001.
- [10] David B. Fogel, Timothy J. Hays, Sarah L. Hahn, and James Quon. Further evolution of a self-learning chess program. In *Proceedings of the IEEE Symposium on Computational Intelligence and Games*, Piscataway, NJ, 2005. IEEE.
- [11] Brad Fullmer and Risto Miikkulainen. Using marker-based genetic encoding of neural networks to evolve finite-state behaviour. In Francisco J. Varela and Paul Bourguine, editors, *Toward a Practice of Autonomous Systems: Proceedings of the First European Conference on Artificial Life*, pages 255–262. MIT Press, Cambridge, MA, 1992.
- [12] Faustino Gomez, Doug Burger, and Risto Miikkulainen. A neuroevolution method for dynamic resource allocation on a chip multiprocessor. In *Proceedings of the INNS-IEEE International Joint Conference on Neural Networks*, pages 2355–2361, Piscataway, NJ, 2001. IEEE.
- [13] Faustino Gomez and Risto Miikkulainen. Incremental evolution of complex general behavior. *Adaptive Behavior*, 5:317–342, 1997.
- [14] Brian Greer, Henri Hakonen, Risto Lahdelma, and Risto Miikkulainen. Numerical optimization with neuroevolution. In *Proceedings of the 2002 Congress on Evolutionary Computation*, pages 361–401, Piscataway, NJ, 2002. IEEE.
- [15] Christian Igel. Neuroevolution for reinforcement learning using evolution strategies. In *Proceedings of the 2003 Congress on Evolutionary Computation*, pages 2588–2595, 2003.
- [16] Yong Liu, Xin Yao, and Tetsuya Higuchi. Evolutionary ensembles with negative correlation learning. *IEEE Transactions on Evolutionary Computation*, 4:380–387, 2000.
- [17] J. R. McDonnell and D. Waagen. Evolving recurrent perceptrons for time-series modeling. *IEEE Transactions on Evolutionary Computation*, 5:24–38, 1994.
- [18] Paul McQuesten. *Cultural Enhancement of Neuroevolution*. PhD thesis, Department of Computer Sciences, The University of Texas at Austin, Austin, TX, 2002. Technical Report AI-02-295.
- [19] David J. Montana and Lawrence Davis. Training feedforward neural networks using genetic algorithms. In *Proceedings of the 11th International Joint Conference on Artificial Intelligence*, pages 762–767. San Francisco: Kaufmann, 1989.
- [20] David E. Moriarty. *Symbiotic Evolution of Neural Networks in Sequential Decision Tasks*. PhD thesis, Department of Computer Sciences, The University of Texas at Austin, 1997. Technical Report UT-AI97-257.
- [21] David E. Moriarty and Risto Miikkulainen. Discovering complex Othello strategies through evolutionary neural networks. *Connection Science*, 7(3):195–209, 1995.
- [22] David E. Moriarty and Risto Miikkulainen. Forming neural networks through efficient and adaptive co-evolution. *Evolutionary Computation*, 5:373–399, 1997.
- [23] David Pardoe, Michael Ryoo, and Risto Miikkulainen. Evolving neural network ensembles for control problems. In *Proceedings of the Genetic and Evolutionary Computation Conference*, 2005.
- [24] Mitchell A. Potter and Kenneth A. De Jong. Cooperative coevolution: An architecture for evolving coadapted subcomponents. *Evolutionary Computation*, 8:1–29, 2000.
- [25] Joseph Reisinger, Kenneth O. Stanley, and Risto Miikkulainen. Evolving reusable neural modules. In *Proceedings of the Genetic and Evolutionary Computation Conference*, 2004.
- [26] Thomas Philip Runarsson and Magnus Thor Jonsson. Evolution and design of distributed learning rules. In *Proceedings of The First IEEE Symposium on Combinations of Evolutionary Computation and Neural Networks*, pages 59–63, Piscataway, NJ, 2000. IEEE.
- [27] Kenneth O. Stanley. *Efficient Evolution of Neural Networks Through Complexification*. PhD thesis, Department of Computer Sciences, The University of Texas at Austin, Austin, TX, 2003.
- [28] Kenneth O. Stanley, Bobby Bryant, and Risto Miikkulainen. Real-time neuroevolution in the NERO video game. *IEEE Transactions on Evolutionary Computation*, 9:653–668, 2005.
- [29] Kenneth O. Stanley and Risto Miikkulainen. Evolving neural networks through augmenting topologies. *Evolutionary Computation*, 10:99–127, 2002.
- [30] Kenneth O. Stanley and Risto Miikkulainen. Competitive coevolution through evolutionary complexification. *Journal of Artificial Intelligence Research*, 21:63–100, 2004.
- [31] Kenneth O. Stanley and Risto Miikkulainen. Evolving a roving eye for go. In *Proceedings of the Genetic and Evolutionary Computation Conference*, 2004.

32-1

32-2

32-3

32-4

- [32] David S. Touretzky, Jeffrey L. Elman, Terrence J. Sejnowski, and Geoffrey E. Hinton, editors. *Proceedings of the 1990 Connectionist Models Summer School*. San Francisco: Kaufmann, 1990.
- [33] Joseba Urzelai, Dario Floreano, Marco Dorigo, and Marco Colombetti. Incremental robot shaping. *Connection Science*, 10:341–360, 1998.
- [34] Alex v. E. Conradie, Risto Miikkulainen, and C. Aldrich. Adaptive control utilising neural swarming. In *Proceedings of the Genetic and Evolutionary Computation Conference*. San Francisco: Kaufmann, 2002.
- [35] Alex v. E. Conradie, Risto Miikkulainen, and C. Aldrich. Intelligent process control utilizing symbiotic memetic neuro-evolution. In *Proceedings of the 2002 Congress on Evolutionary Computation*, 2002.
- [36] Shimon Whiteson, Nate Kohl, Risto Miikkulainen, and Peter Stone. Evolving keepaway soccer players through task decomposition. *Machine Learning*, 59:5–30, 2005.
- [37] Shimon Whiteson, Peter Stone, Kenneth O. Stanley, Risto Miikkulainen, and Nate Kohl. Automatic feature selection in neuroevolution. In *Proceedings of the Genetic and Evolutionary Computation Conference*, 2005.
- [38] Darrell Whitley, Stephen Dominic, Rajarshi Das, and Charles W. Anderson. Genetic reinforcement learning for neurocontrol problems. *Machine Learning*, 13:259–284, 1993.
- [39] Alexis P. Wieland. Evolving controls for unstable systems. In Touretzky et al. [32], pages 91–102.
- [40] Xin Yao. Evolving artificial neural networks. *Proceedings of the IEEE*, 87(9):1423–1447, 1999.

32-5

- [41] Chern Han Yong and Risto Miikkulainen. Cooperative coevolution of multi-agent systems. Technical Report AI01-287, Department of Computer Sciences, The University of Texas at Austin, 2001.

32-6