Evolutionary Design of Neural Architectures — A Preliminary Taxonomy and Guide to Literature

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Abstract

This report briefly motivates current research on *evolutionary design of neural architectures* (EDNA) and presents a short overview of major research issues in this area. It also includes a preliminary *taxonomy* of research on EDNA and an extensive bibliography of publications on this topic. The taxonomy is an attempt to categorize current research on EDNA in terms of major research issues addressed and approaches pursued. It is our hope that this will help identify open research questions as well as promising directions for further research on EDNA. The report also includes an appendix that provides some suggestions for effective use of the electronic version of the bibliography.

1 Introduction

Artificial neural networks [Rumelhart & McClelland, 1986, Grossberg, 1988, Gallant, 1993, Kung, 1993, Haykin, 1994, Honavar & Uhr, 1994] offer an attractive paradigm for the design and analysis of adaptive, intelligent systems for a broad range of applications in artificial intelligence and cognitive modeling for a number or reasons including: potential for massively parallel computation, robustness in the presence of noise, resilience to the failure of components, amenability to adaptation and learning (by the modification of computational structures employed), and resemblance (albeit superficial) to biological neural networks (brains).

Despite much research activity in this area which has led to the discovery of several significant theoretical and empirical results and the development of important practical applications over the past decade(s), the design of artificial neural networks (ANN) for specific applications, under given sets of design constraints (for example, those dictated by particular computer technologies) is, to a large extent, a process of trial and error, relying mostly on past experience with similar applications. Furthermore, the performance (and cost) of ANN on particular problems is critically dependent, among other things, on the choice of primitives (neurons or processing elements), network architecture and the learning algorithm(s) used. For example, many of the popular learning algorithms used in ANN essentially search for a suitable setting of modifiable parameters (also called weights) within an otherwise a-priori specified network topology under guidance from sample inputs (training samples) from the task environment. Clearly, in order for this approach to succeed, the desired setting of parameters must in fact exist within the space being searched (which in turn is constrained by the choice of network topology) and the search algorithm used must in fact be able to find it [Honavar & Uhr, 1993]. Even when a suitable setting of parameters can be found using such an approach, the ability of the resulting network to generalize on data not seen during learning [Kung, 1993, Haykin, 1994] or the cost of the hardware realization or the cost of using the network (as measured by its size, power consumption etc.) may be far from optimal. These factors make the process of ANN design difficult. In addition, the lack of sound design principles constitutes a major hurdle in the development of large scale ANN systems for a wide variety of practical problems.

Thus, techniques for automating the design of neural architectures for particular classes of problems under a wide variety of design and performance constraints are clearly of interest. Motivated by this, some researchers have recently begun to investigate *constructive* or *generative* neural network learning algorithms that extend the search for the desired input-output mapping to the space of appropriately constrained network topologies by incrementally constructing the required network [Gallant, 1993, Honavar & Uhr, 1993, Honavar, 1994]. Against this background, a logical next step is the exploration of more powerful techniques for efficiently searching the space of network architectures.

Thus, the design of neural architectures presents us with a challenging multi-criterion optimization problem, namely, that of searching for neural architectures (and learning algorithms) for particular classes of applications (e.g., 2-and-3-dimensional visual pattern classification, diagnosis, language processing, grammar inference, signal detection, sensor fusion, inductive and deductive inference, adaptive control, planning, robotics, etc). Evolutionary algorithms [Holland, 1975, Fogel et al, 1966, Goldberg, 1989, Koza, 1992, Michalewicz, 1992] offer an attractive and relatively efficient, randomized opportunistic approach to search for near-optimal solutions in a variety of problem domains. The design of efficient neural architectures for specific classes of problems under given sets of design and performance constraints is therefore a natural candidate for the application of evolutionary algorithms.

In addition to the development of new and powerful techniques for neural engineering, exploration of evolutionary approaches to the design of neural architectures is likely to shed light on important open problems in artificial intelligence, cognitive modeling, and biology — for, no theory of cognition can be complete without a detailed specification of the mechanisms that explain the evolution of structures and processes (computational or otherwise) that exhibit intelligence.

At an abstract level, the neural network design problem is essentially an instance of the *program synthesis* task not very different from that explored by researchers in artificial intelligence [Uhr, 1963, Uhr, 1973] and genetic programming[Koza, 1992, Fogel et al, 1966]. Such techniques offer an attractive (and often, the only) approach to finding solutions to complex problems where neither the shape (detailed structure) nor the size of the solutions is known in advance. What distinguishes evolutionary design of neural architectures from such general methods for program synthesis is is the commitment to a particular class of computing structures, namely massively parallel, highly interconnected networks of relatively simple processing elements (or ANN) as opposed to, say, `LISP` programs. Given the equivalence of several models of computation (including *lambda calculus* of `LISP` programs, *Turing machines*, *Post productions* on which the knowledge-based expert systems are based), the choice of any given model is mostly a matter of convenience. Some models are better suited to expressing certain classes of computations than others and may have some cost/performance advantages over others given particular implementation media. It is well known that virtually any program can be realized by an artificial neural network (even a rather simple one such as that built from *threshold logic units* or McCulloch-Pitts neurons [McCulloch & Pitts, 1943]). Artificial neural networks represent a particularly attractive model of computation for a broad range of problems in artificial intelligence and cognitive modeling [Honavar & Uhr, 1994, Honavar, 1994, Honavar & Uhr, 1995]. Furthermore, the study of designs for such neural architectures provides a useful research strategy for exploring answers to many fundamental questions of interest in neuroscience including: *What are the programs of the brain? How are they realized given specific sets of design and performance constraints? How does the brain get wired or programmed through learning or evolution to compute the things that it does?*, etc.

This report is an attempt to put together a fairly up-to-date bibliography and a tentative taxonomy of current research on the evolutionary design of neural architectures. It does not provide a comprehensive review of the vast amount of research in this area. The reader is referred to [Weiss, 1990, Yao, 1993, Honavar, 1995, Balakrishnan & Honavar, 1995b] for such reviews. The primary purpose of the taxonomy presented here is to categorize current research in evolutionary design of neural networks in a manner that would be helpful in bringing out the similarities and differences among different approaches to problems in this area. It is our first attempt to identify some key research problems and approaches to their solution within a common framework (provided by the taxonomy). We feel that the time is ripe for such an undertaking given the vast number and diversity of recent research papers on this topic. It is our hope that this effort will help us (and other researchers) identify and formulate open research questions as well as topics that need further exploration. Needless to say, given the fast-moving nature of this field, the taxonomy that is presented here would almost certainly evolve and get more refined as new research directions are explored.

2 Evolutionary Design of Neural Architectures

The key processes in the evolutionary approach to the design of neural architectures are shown in Figure 1.

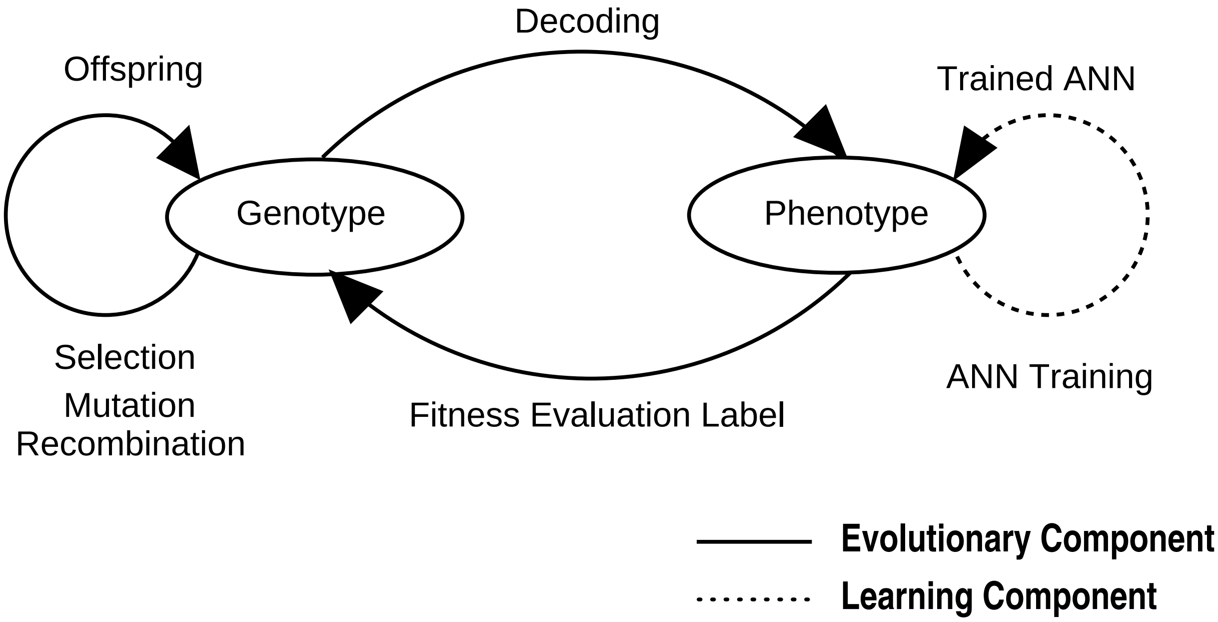

Figure 1: Process of Evolutionary Design of Artificial Neural Networks

Evolutionary algorithms [Holland, 1975, Fogel et al, 1966, Goldberg, 1989, Koza, 1992, Michalewicz, 1992] are loosely modeled on processes that appear to be at work in biological evolution and the working of the immune systems. Central to such evolutionary systems is the idea of a population of *genotypes* that are elements of a high dimensional search space. For example, in simple genetic algorithms [Goldberg, 1989], *genotypes* are binary strings of some fixed length (say n) that code for points in an n-dimensional Boolean search space.

More generally, a genotype can be thought of as an arrangement (e.g., a string) of *genes*, where each gene takes on values from a suitably defined domain of values (also known as *alleles*). Each genotype encodes for typically one, but possibly a set of *phenotypes* or candidate solutions in the domain of interest — in our case, a class of neural architectures. Such encodings might employ genes that take on numeric values for a few parameters or complex symbol structures that are transformable into phenotypes (in this case, neural networks) by appropriate *decoding* processes. This decoding process may be extremely simple or fairly *involved* (as appears to be the case in mammalian brain development). These resulting neural networks (i.e., the phenotypes) may also be equipped with learning algorithms that train it using the environmental stimuli or simply evaluated on the given task (assuming the weights of the network are also determined by the encoding/decoding mechanism). This evaluation of a phenotype determines the *fitness* of the corresponding genotype.

The evolutionary procedure works on a population of such genotypes, preferentially selecting genotypes that code for high fitness phenotypes and reproducing them. *Genetic operators* such as *mutation*, *crossover*, *inversion* etc., are used to introduce variety into the population and to sample variants of candidate solutions represented within the current population. Thus, over several generations, the population gradually *evolves* toward genotypes that correspond to high fitness phenotypes.

Over the past decade, several researchers have investigated the use of evolutionary search techniques for automating the design of artificial neural networks. Most of these studies have been exploratory in nature and much systematic work is needed to identify the strengths and limitations of the various approaches. More importantly, sound scientific principles need to be discovered, to guide the development and application of evolutionary techniques in the design of artificial neural architectures for specific classes of problems (given a variety of design and performance constraints).

3 Towards a Taxonomy of Evolutionary Design of Neural Architectures

This section develops a preliminary taxonomy of research on evolutionary approaches to the design of artificial neural architectures. The proposed taxonomy is suggested by what we see as the key problems explored and solutions proposed in a number of publications on this topic. In turn, the taxonomy provides a way of organizing the published literature on EDNA into a bibliography, that together with the taxonomy, provides a useful guide to literature on this topic. (See Appendix I for details on the organization and use of the bibliography).

3.1 Genotype Representation

The question of *how* a neural architecture is represented as a genotype is critical to the working of an evolutionary ANN design system. The representation or *encoding* used not only determines the classes of neural architectures that could possibly evolve but also constrains the choice of the *decoding* process. For example, if the problem at hand requires the discovery of neural networks with a *recurrent* structure, in order to ensure non-zero probability of success, the encoding scheme must be expressive enough to describe recurrent neural architectures, and the decoding mechanism must be capable of transforming such a description into an appropriate recurrent network (phenotype).

A broad range of choices (with varying degrees of efficiency, robustness, etc.) may exist for both the encoding and decoding schemes.

An examination of encoding and decoding schemes employed by numerous researchers in their work suggests that genotype representations may be broadly classified into two categories based on the decoding effort that is needed:

- **Direct Encodings** that require little effort to decode i.e., the transformation of the genotype into a phenotype is rather trivial. An example of such an encoding is a *connection matrix* that precisely and directly specifies the architecture of the corresponding neural network.

- **Indirect Encodings** that require considerable decoding effort in the construction of a phenotype. An example of such an encoding is one that uses rewrite rules to specify a set of construction rules that are recursively applied to yield the phenotype. Indirect encodings used in the literature fall into two broad categories — *grammatical* encodings (cellular grammars, graph grammars, genetic/biological grammars, geometric grammars etc) and *others* (genetic programming paradigm i.e., LISP programs, development models etc).

Other categorizations of encoding schemes are possible including: *deterministic* versus *stochastic*, *hierarchical* versus *non-hierarchical*, *modular* versus *non-modular*, etc. The interested reader is refered to [Balakrishnan & Honavar, 1995a] for a characterization of the properties of genetic representations of neural architectures.

3.2 Network Topology or Structure of the Phenotypes

It is well known that the success of a neural architecture in solving a particular problem (or class of problems) critically depends on the network topology (or the structure of the phenotype in our evolutionary design system). For example, a purely *feed-forward* neural network is incapable of discovering or responding to temporal dependencies in its environment; a *recurrent* network is needed for this task. Similarly, *non-linear* decision boundaries cannot be discovered by 1-layer networks (e.g. perceptrons); multi-layer perceptrons are required. It is therefore useful to classify work in evolutionary design of neural architectures based on the classes of neural network topologies that are evolved. Neural network topologies may be classified into two broad types:

- **feed-forward** networks (those without feedback loops); and

- **recurrent** networks (those with feedback loops).

Each of the two basic types of topologies may be further classified as networks that are — *multi-layered*, *strictly layered*, *randomly connected*, *locally connected*, *sparsely connected*, *fully connected*, *regular*, *irregular*, *modular*, *hierarchical* etc.

The choice of the target class of network structures dictates the choice of genetic representation. This is very much analogous to the choice of the *knowledge representation* *scheme* for problem solving using *state-space* search in artificial intelligence. Thus, much can be gained in terms of search efficiency by restricting the search space based on a-priori knowledge about the properties of the solution set. In evolutionary design of neural architectures, one way to do this is to choose a sufficiently restricted class of network topologies based on knowledge of the problem domain. Without such bias, much of the search effort can be wasteful.

Additional requirements on the structure of the solution to a neural network design problem may be dictated by cost and/or performance considerations in the context of a particular technology. For example, a VLSI designer would prefer locally connected, fault-tolerant, highly modular neural network structures over globally connected, non-modular ones [Mead, 1989, Uhr, 1984, Honavar & Uhr, 1989, Kung, 1993].

Hence, network structure or topology, can be effectively used to classify different approaches to the evolutionary design of neural architectures.

3.3 Variables of Evolution

Neural architectures are typically specified in terms of the topology (or connectivity pattern), functions computed by the neurons (e.g., *threshold*, *sigmoid*, etc.) and the connection weights (or, a learning algorithm that sets the weights) [Rumelhart & McClelland, 1986, Kung, 1993, Gallant, 1993, Haykin, 1994]. A more complete description of a neural architecture requires the specification of coordination and control structures and learning structures (among other things) [Honavar, 1990, Uhr, 1990, Honavar & Uhr, 1990, Honavar, 1994, Honavar, 1994, Honavar, 1995]. Virtually any subset of these variables are candidates to be operated on by evolutionary processes. For example, a system $\mathcal{A}$ might evolve the network connectivity *as well as* the weights (while maintaining everything else constant) whereas a system $\mathcal{B}$ might only evolve the connectivity, relying on a perhaps more efficient *local* search for weights within each network. The time/performance tradeoffs for the two systems, on the given problem, will be different, making the choice of variables subjected to evolution, an extremely critical factor.

In addition to the network connectivity and the weights, one might evolve a learning algorithm, control or regulatory functions, the functions computed by various neurons, distribution of different types of neurons, relative densities of connections, parameters (and or processes) governing the decoding of a genotype into a phenotype, and so on. Thus, the variables subjected to evolution, form a useful classification scheme for work in the area of evolutionary design of neural architectures.

3.4 Application Domain

Much of the work on evolutionary design of neural architectures is driven by particular engineering applications (e.g., design of networks for pattern classification, control, robot navigation, sensor fusion, VLSI implementations of problem-specific neural architectures, etc.) and/or specific scientific hypothesis (e.g., explanations for evolution of certain classes of modular organization or prevalence of particular network structures and functional units in mammalian brains across different species, etc.). In this context, attempts to understand and characterize to the extent possible, the relationship between properties of classes of application problems and those of the ANN used in its solution are of great theoretical and practical interest. Classification of evolutionary approaches to the design of neural architectures based on their focus on particular application domains is a step in this direction.

3.5 An Illustrative Example of the Use of the Proposed Taxonomy

This section demonstrates through an example, the use of the EDNA taxonomy outlined in the previous section.

Our example is drawn from [Miller et al, 1989]. In this scheme, the architecture of a network of N units is represented by a *connectivity constraint matrix*, C of dimension $N \times (N+1)$, with the first N columns specifying the constraints on the connections between the N units, and the final column denoting the constraint on the *threshold bias* of each unit.

Each entry C_{ij}, of the connectivity constraint matrix indicates the nature of the constraint on the connection from unit j to unit i (or the constraint on the threshold bias of unit i if $j = N+1$). In their implementation, the authors allow each matrix entry to take on one of two possible values — 0 denoting the *absence*, and 1 indicating the presence — of a *trainable* connection between the corresponding units.

Given the connectivity constraint matrix, the genotype is constructed by concatenating the rows of the matrix, to yield a bit-string of length $N \times (N+1)$. This is illustrated in Figure 2.

The genetic algorithm maintains a population of such bit-strings (each of length $N \times (N+1)$). Each string codes for a network architecture. A *fitness-proportionate* selection scheme chooses parents for reproduction — *crossover* swaps rows between parents, while *mutation* randomly flips bits in the connectivity constraint matrix with some *low*, pre-specified probability.

To determine the fitness of a genotype the architecture it encodes is first constructed by providing connections corresponding to matrix entries of 1, and not making any connections for the 0 entries (all feedback connections are ignored even though they may be specified in the genotype — thus this system evolves pure feed-forward networks). The connections in the network are then set to small random values, and trained for a fixed number of epochs using the back-propagation learning rule. The *total sum squared error* $\mathcal{E}$ of the network, at the end of the learning phase, is then used as the *fitness* measure, with *low* values of $\mathcal{E}$ corresponding to better learning of the task and hence a higher fitness label for the corresponding genotype.

The authors report results for the XOR problem (2-bit parity), the four-quadrant problem (a generalization of the XOR problem from binary inputs to real inputs) and

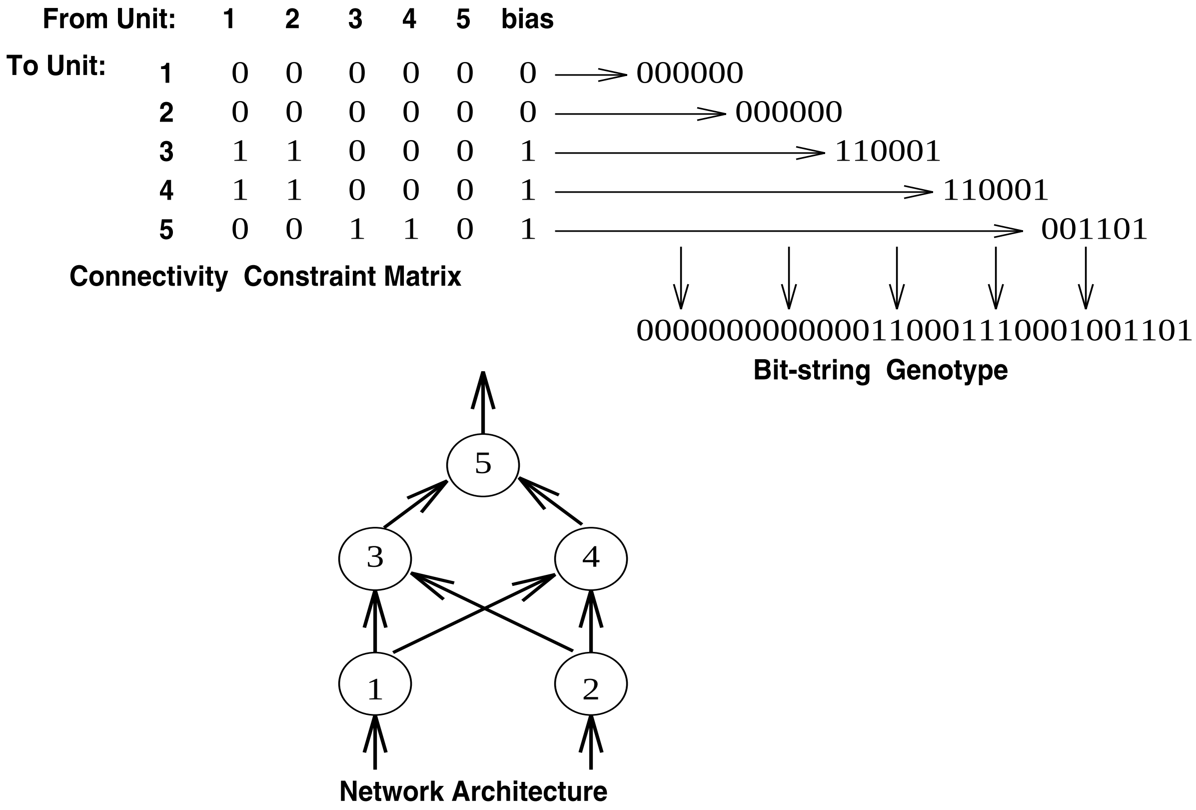

Figure 2: Evolutionary Design of Neural Networks — An example from [Miller et al., 1989]

the pattern copying problem (the network simply copies the input onto the output — note that hidden units are not required for this task).

Now let us see how this approach fits into the EDNA taxonomy that was outlined in section 3.

This system uses a constraint matrix to specify the network connectivity. The genotype is a simple concatenation of the rows of this matrix. Decoding the genotype to construct the phenotype is a trivial process, requiring little more than reading of the matrix elements. Thus, as per our taxonomy, this system uses *direct encoding.*

Further, feedback connections are ignored by the decoding process hence only networks with *feed-forward* topology are evolved by this system.

Also, the only variable subjected to evolution is the *connectivity* (or the topology) of the network, the *parameters* (connection weights) are determined separately by the back-propagation procedure and are not subject to evolution.

Finally, the system was tested on three *toy* problems —*XOR, four-quadrant problem* and the *pattern copying problem*, which form its application domain.

The example discussed above illustrates the use of the proposed taxonomy to categorize current research on EDNA. It is our hope that it will also help identify open research problems and new research directions in this area.

4 Epilogue

This report has attempted to: motivate research on evolutionary approaches to the design of neural architectures (EDNA); classify current research in this area in terms of a preliminary taxonomy; and provide a guide to literature on EDNA in the form of a bibliography. Appendix I explains the organization of the bibliography and offers suggestions for using it effectively.

We have made every attempt to make the bibliography as complete as possible, however, we are almost certain that it contains gaps in its coverage of the literature on EDNA. We would welcome updates, additions and suggestions for keeping it up-to-date.

Though the bibliography contains over 300 entries, we have been able to label only a small fraction of them, primarily because we lack detailed knowledge of the contents of many of the publications included in it. We would appreciate input from the readers to help us completely label all the entries in the bibliography.

Acknowledgements

The entries in this bibliography were obtained either through our personal forays into the literature, or by researchers on our GANN[1] mailing list. In particular, we would like to thank David Moriarty, Nikolaus Almassy, Frederic Gruau, Michel Olivier, Robert Smith, Filippo Menczer, Georg Thimm, Dan Adler, Peter Dudey, Dave Opitz, Larry Yaeger, Martin Mandischer , Jari Vaario, Russell Anderson, Riccardo Poli, Peter Hancock, Javier Marin, Frank Amos, Egbert Boers, Spyros Kazarlis and Johannes Schäfer for sending us relevant bibliographic references. We have also drawn on earlier bibliographies on this topic [Rudnick, 1990, Schaffer, 1994].

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[1]GANN: Genetic Algorithms and Neural Networks Mailing List.
To subscribe, send e-mail to — `gann-request@cs.iastate.edu` with "subject" `subscribe`.

References

[Balakrishnan & Honavar, 1995a] Balakrishnan, K. & Honavar, V. Analysis of Genetic Representations and Operators With Applications in Evolutionary Design of Neural Architectures. In preparation.

[Balakrishnan & Honavar, 1995b] Balakrishnan, K. & Honavar, V. Evolutionary Design of Neural Architectures. In preparation.

[Fogel et al, 1966] Fogel, L., Owens, A. & Walsh, M. Artificial Intelligence through Simulated Evolution. New York, NY: John Wiley & Sons.

[Gallant, 1993] Gallant, S. Neural Networks and Expert Systems. Cambridge, MA: MIT Press.

[Goldberg, 1989] Goldberg, D. Genetic Algorithms in Search, Optimization and Machine Learning. Reading, MA: Addison-Wesley.

[Grossberg, 1988] Grossberg, S. (Ed). Neural Networks and Natural Intelligence. Cambridge, MA: MIT Press.

[Haykin, 1994] Haykin, S. Neural Networks. New York, NY: Macmillan.

[Holland, 1975] Holland, J. Adaptation in Natural and Artificial Systems. Ann Arbor, MI: University of Michigan Press.

[Honavar, 1990] Honavar, V. Generative Learning Structures for Generalized Connectionist Networks. Ph.D. Dissertation. University of Wisconsin, Madison, Wisconsin.

[Honavar, 1994] Honavar, V. Toward Learning Systems That Use Multiple Strategies and Representations. In: *Artificial Intelligence and Neural Networks: Steps Toward Principled Integration.* Honavar, V. & Uhr, L. (Ed.). San Diego, CA: Academic Press.

[Honavar, 1994] Honavar, V. Symbolic Artificial Intelligence and Numeric Artificial Neural Networks: Toward a Resolution of the Dichotomy. In: *Computational Architectures Integrating Symbolic and Neural Processes.* Sun, R. & Bookman, L. (Ed.) New York: Kluwer.

[Honavar, 1995] Honavar, V. Evolutionary Design of Neural Architectures. Book in preparation.

[Honavar, 1995b] Honavar, V. & Uhr, L. Symbolic Artificial Intelligence, Artificial Neural Networks, and Beyond. In: *Hybrid Intelligent Systems.* Goonatilake, S. & Khebbal, S. (Ed.) London: Wiley.

[Honavar & Uhr, 1989] Honavar, V. & Uhr, L. Brain-Structured Networks That Perceive and Learn. *Connection Science* 1 139-160.

[Honavar & Uhr, 1990] Honavar, V. & Uhr, L. Coordination and Control Structures and Processes: Possibilities for Connectionist Networks. *Journal of Experimental and Theoretical Artificial Intelligence* 2 277-302.

[Honavar & Uhr, 1993] Honavar, V. & Uhr, L. Generative Learning Structures and Processes for Generalized Connectionist Networks. *Information Sciences* (Special Issue on Artificial Intelligence and Neural Networks) 70 75-108.

[Honavar & Uhr, 1994] Honavar, V. & Uhr, L. (Ed.). Artificial Intelligence and Neural Networks: Steps Toward Principled Integration. San Diego, CA: Academic Press.

[Honavar & Uhr, 1995] Honavar, V. & Uhr, L. Symbolic Artificial Intelligence, Connectionist Networks, and Beyond. In: *Intelligent Hybrid Systems.* Goonatilake, S. & Khebbal, S. (Ed.) London: Wiley.

[Koza, 1992] Koza, J. Genetic Programming. Cambridge, MA: MIT Press.

[Kung, 1993] Kung, S. Digital Neural Networks. New York, NY: Prentice Hall.

[McCulloch & Pitts, 1943] McCullcoh, W. S., & Pitts, W. H. A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics* 5 115-133.

[Mead, 1989] Mead, C. Analog VLSI and Neural Systems. Reading, MA: Addison-Wesley.

[Michalewicz, 1992] Michalewicz, Z. Genetic Algorithms + Data Structures = Evolution Programs. New York, NY: Springer-Verlag.

[Miller et al, 1989] Miller, G., Todd, P. & Hegde, S. Designing Neural Networks Using Genetic Algorithms. *Proceedings of the Third International Conference on Genetic Algorithms* 379-384.

[Rudnick, 1990] Rudnick, M. A Bibliography: The Intersection of Genetic Search and Artificial Neural Networks. Technical Report CSE-90-001, Department of Computer Science and Engineering, Oregon Graduate Institute.

[Rumelhart & McClelland, 1986] Rumelhart, D. & McClelland, J. (Ed.). Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Cambridge, MA: MIT Press/Bradford Books.

[Schaffer, 1994] ENCORE Bibliography on Combinations of Genetic Algorithms and Neural Networks (COGANN). Maintained at EClair sites.

[Uhr, 1963] Uhr, L. & Vossler, C. A Pattern Recognition Program That Generates, Evaluates, and Adjusts its Own Operators. In: *Computers and Thought.* Feigenbaum, E. & Feldman, J. (Ed.) New York: McGraw-Hill.

[Uhr, 1973] Uhr, L. Pattern Recognition, Learning, and Thought. Englewood Cliffs, NJ: Prentice Hall.

[Uhr, 1984] Uhr, L. Algorithm-Structured Computer Arrays and Networks. New York: Academic Press.

[Uhr, 1990] Uhr, L. Increasing the Power of Connectionist Networks by Improving Structures, Processes and Learning. *Connection Science* 2 179-193.

[Weiss, 1990] Weiss, G. Combining Neural and Evolutionary Learning: Aspects and Approaches. Technical Report FKI-132-90, Technical University of Munich, West Germany.

[Yao, 1993] Yao, X. A Review of Evolutionary Artificial Neural Networks. In *International Journal of Intelligent Systems* 8(4) 539-567.

Appendix I
Organization and Use of the EDNA Bibliography

The bibliography is organized (primarily) according to the taxonomy developed in section 3. The individual entries in the bibliography are labeled according to the various categories in the taxonomy (see below for details), making it easier to locate bibliographic entries that deal with specific aspects of EDNA. The following sections explain how to obtain an electronic version of the bibliography along with some suggestions for its effective use.

Obtaining an Electronic Version of the Bibliography

The compressed `.bib` file containing the bibliography is available through anonymous ftp at `ftp.cs.iastate.edu` as `pub/gann/bib/gann.bib.Z`. The file `pub/gann/bib/README` contains useful tips on how to search the bibliography using key words etc.

Alternatively, the bibliography may be accessed on the `World-Wide Web` (`WWW`) using a suitable `WWW` browser such as `Mosaic` via the `URL`:

`http://www.cs.iastate.edu/˜gannadm/homepage.html` .

Organization of the Bibliography

This bibliography is an attempt to put together as complete a collection as possible of publications on the evolutionary design of neural networks, organized roughly according to the taxonomy outlined in section 3. Each entry in the bibliography has been *labeled* depending on how that work addresses each of the four issues raised in section 3 — *genotype representation*, *network topology*, *variables of evolution* and *application domain*. In addition, we allow an additional label based on *network type*, mainly for pragmatic reasons — to facilitate search for bibliographic entries corresponding to specific popular network types like *multi-layer perceptrons* or *Boltzmann machines* or *Hopfield networks* etc. Thus, each *label* has 5 components, each component having the format:

`<Key> = {<set of values>}` .

The five keys we use are — *encoding, topology, evolves, applications* and *network*, one for each of the issues listed above. For example, if the label of an entry in the bibliography includes the string "`topology = {recurrent}`", then the entry deals with the evolution of recurrent networks. Similarly the string "`evolves = {parameters}`", indicates that the corresponding entry describes an EDNA system with the network parameters (weights etc.) as the variables of evolution, and so on.

Currently, the bibliography is organized to support search on the basis of specified values for each of the 5 *keys* which can (at present) take on values from the domains specified below. Note that new values (and even keys) can be easily added to this system.

- **encoding** — direct, indirect, classifier systems, L-systems, graph grammars, grammar based, cellular encoding, LISP programs, developmental.

- **topology** — feed-forward, recurrent, multi-layered, locally connected, modular, randomly connected, regular, irregular, strictly layered, general(both feed-forward and recurrent).

- **evolves** — parameters, connectivity, topology, learning rule, size, construction rules, receptive fields, problem decomposition, feature detectors.

- **applications** — parity, encoder-decoder, contiguity, optimization, controller, simulated world, pattern recognition, speech recognition, image recognition, cognitive maps, temporal pattern recognition, game playing, function approximation, face recognition, digit recognition, language recognition, neurobiological modeling, data compression, travelling salesperson problem, regular language inference, binary mapping, time-series, pattern copying, four-quadrant.

- **network** — perceptron, multi-layer perceptron, self-organizing, kohonen, boltzmann, product-unit, radial basis function, counterpropagation, jordan, elman.

This labeling scheme provides a simple and effective way to search for bibliography entries that fall in any of the categories in the taxonomy outlined in section 3. The procedure for searching the bibliography and extracting relevant entries is outlined in the sections that follow.

Locating Specific Information in the Bibliography

The labeling scheme outlined in the previous section makes it possible to locate entries in the bibliography that fall in one or more categories specified by the values of the *keys*. For example, all entries that deal with *feed forward* neural networks will have as part of their label, the string "`topology = {feed forward}`", while those that deal with *recurrent* ones will have the label — "`topology = {recurrent}`". One of the simplest (although not the most convenient) ways to use the bibliography is to use a standard text editor and perform a *pattern search* for whatever is of interest. For example, if one is interested in work on evolving *recurrent* networks, he/she can simply search for entries that contain as part of their labels, a pattern of the form — "`topology = {recurrent}`" using virtually any text editor (e.g., `vi` or *emacs*).

The drawback of this approach is that unless the search string provided is exactly like the string in the label, the search query will fail. For example, search for — "`topology = { recurrent}`" will fail owing to the additional spaces in the search query string.

This problem becomes particularly critical for labels which have keys with multiple values. For example, any work dealing with evolving neural networks using the genetic programming paradigm (LISP programs), will have the *encoding* key labeled as — "`encoding = {indirect, LISP programs}`". Here, one needs to specify the complete string in order to search effectively (partial string searches, like — "`encoding = {LISP programs}`", will fail to produce the desired response).

These problems can be overcome by using a more sophisticated search facility, in particular, something that works with *.bib* files. One such utility — `bibview` — provides all the functions we desire and more importantly, is available as a free, public domain utility on the internet. The next subsection provides pointers to obtaining and using `bibview` to perform efficient searches in the bibliography.

Obtaining and Using `bibview`

`Bibview` is available by anonymous ftp from: `sunsite.unc.edu`, as the file
`pub/packages/TeX/biblio/bibtex/utils/bibview-2.0/bibview-2.1.tar.gz.`
You will need to uncompress the file using `gunzip`, extract the files using `tar`, and install `bibview` on your system. The package works *as is*, on HP 9000/710 running HP/UX, DECstation 2100 and MicroVax II running ULTRIX and on SUN running SunOS 4.1. For other platforms, one might have to make specific changes to the makefile or contact Armin Liebl (liebla@informaatik.tu-muenchen.de) for help.

Once you have bibview running, you can load your .bib file by clicking on `File` and selecting `Open`. But before you do this, remember to turn off the `Automatic Check` option under `Options` (since quite a few of the entries in this bibliography have incomplete information which would otherwise cause `bibview` to complain of *consistency error*). Once the .bib file is successfully loaded you can:

- *List* all the bibliographic entries in the file and then *Sort* them in whichever order you would like (a whole set of candidate options are available)
- *Print* out the bibliography as a LaTeXdocument to be incorporated in other LaTeXdocuments
- *Search* for specific references
- Add *New* entries etc.

Since the other options are self-explanatory, we will briefly explain the steps involved in searching. For example, to list all entries on recurrent networks, the steps required are:

1. Start `bibview`
2. Click on options, and turn `Automatic Check` off
3. Click on `File` and `Open` the required `.bib` file
4. Once the file is successfully loaded, click on `Search`
5. Now, to locate all entries on recurrent networks, go down to the `Userdefined Fields` and specify `topology` in the keyword section and `recurrent` in the corresponding value section
6. Click on `Start search`

7. `bibview` will return a list of entries from the bibliography that matches your input query, in this case, all entries *labeled* with recurrent networks

Note that filling in more than one keyword section while searching will result in compound searches. For other capabilities of *bibview*, please refer to the `README` and `CHANGES` files accompanying the `bibview` utility. *Please bear in mind that all entries in this bibliography have not yet been completely labeled, hence there may be entries that may not show up in a search (although it is in the bibliography).*

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References

[AAT93] E. Alba, J.F. Aldana, and J.M. Troya. Genetic Algorithms as Heuristics for Optimizing ANN Design. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Proceedings of the International Conference on Artificial Neural Nets and Genetic Algorithms*, pages 683–690. Springer-Verlag, 1993.

[ABP90] C. A. Ankenbrandt, B. P. Buckles, and F. E. Petry. Scene Recognition using Genetic Algorithms with Semantic Nets. *Pattern Recognition Letters*, 11:285–293, April 1990.

[ACFX93] P. Arena, R. Caponetto, I. Fortuna, and M. G. Xibilia. MLP Optimal Topology via Genetic Algorithms. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Proceedings of the International Conference on Artificial Neural Nets and Genetic Algorithms*, pages 670–674. Springer-Verlag, 1993.

[Ack85] David H. Ackley. A Connectionist Algorithm for Genetic Search. In John. J Grefenstette, editor, *Proceedings of the First International Conference on Genetic Algorithms and their Applications*, pages 121–135, Hillsdale, New Jersey, 1985. Lawrence Erlbaum Associates.

[Ack87] David H. Ackley. *A Connectionist Machine for Genetic Hillclimbing*. Kluwer Academic Publishers, Boston, MA, 1987.

[AL92] David H. Ackley and Michael L. Littman. Interactions between Learning and Evolution. In Christopher G. Langton, Charles Taylor, J. Doyne Farmer, and Steen Rasmussen, editors, *Artificial Life II*, pages 487–509. Addison, 1992.

[ARS93] Rudolf F. Albrecht, Colin R. Reeves, and Nigel C. Steele, editors. *Proceedings of the International Conference on Artificial Neural Networks and Genetic Algorithms*. Springer-Verlag, April 14-16 1993.

[ASP94] Peter J. Angeline, Gregory M. Saunders, and Jordan B. Pollack. An Evolutionary Algorithm that Constructs Recurrent Neural Networks. *IEEE Transactions on Neural Networks*, 5:54–64, 1994.

[Aus91] Scott Austin. Genetic Neurosynthesis. In *Proceedings of AIAA Aerospace VIII*, Baltimore, MD, October 1991.

[Bal90] N. Ball. Adaptive Signal Processing via Genetic Algorithms and Self-organizing Neural Networks. In *Proceedings of the IEEE Workshop on Genetic Algorithms, Simulated Annealing and Neural Networks*, University of Glasgow, Scotland, 1990.

[Bal93] N. R. Ball. Towards the Development of Cognitive Maps in Classifier Systems. In *Proceedings of the International Conference on Artificial Neural Nets and Genetic Algorithms*, pages 712–718, 1993.

[BB91] Richard K. Belew and Lashon B. Booker, editors. *Proceedings of the Fourth International Conference on Genetic Algorithms*, San Mateo, CA, July 13-16 1991. University of California, San Diego, Morgan Kaufmann.

[BBC91] Yoshua Bengio, Samy Bengio, and Jocelyn Cloutier. Learning a synaptic learning rule. In *Proceedings of the International Joint Conference on Neural Networks*, page 969, 1991.

[BBM92] F.Z. Brill, D.E. Brown, and W.N. Martin. Fast Genetic Selection of Features for Neural Network Classifiers. *IEEE Transactions on Neural Networks*, 3(2):324–328, March 1992.

[BBUW93] J.M. Bishop, M.J. Bushnell, A. Usher, and S. Westland. Genetic Optimization of Neural Network Architectures for Colour Recipe Prediction. In *Proceedings of the International Conference on Artificial Neural Networks and Genetic Algorithms*, pages 719–725, 1993.

[Bel89a] Richard K. Belew. Evolution, Learning and Culture: Computational Metaphors for Adaptive Algorithms. Cse technical report cs89-156, University of California at San Deigo, La Jolla, CA, September 1989.

[Bel89b] Richard K. Belew. When Both Individuals and Populations Search: Adding Simple Learning to the Genetic Algorithm. In J. D Schaffer, editor, *Proceedings of the Third International Conference on Genetic Algorithms*, pages 34–41. ICGA89, Morgan Kaufmann, 1989.

[Ber88] Aviv Bergman. Variation and Selection: An Evolutionary Model of Learning in Neural Networks. *Neural Networks*, 1(1):75–, 1988.

[Ber89] Aviv Bergman. Self-Organization by Simulated Evolution. In E. Jen, editor, *Lectures in Complex Systems: Proceedings of the 1989 Complex Systems Summer School*, Santa Fe, 1989.

[Bes92] P. Bessiere. Genetic Algorithms Applied to Formal Neural Networks: Parallel Genetic Implementation of a Boltzmann Machine and Associated Robotic Experimentations. In F.J. Varela and P. Bourgine, editors, *Toward a Practice* *of Autonomous Systems: Proceedings of the First European Conference on Artificial Life*, pages 310–314, Cambridge, MA, USA, 1992. MIT Press.

[BG92a] Randall D. Beer and John C. Gallagher. Evolving Dynamical Neural Networks for Adaptive Behavior. *Adaptive Behavior*, 1(1), 1992.

[BG92b] Stephan Bornholdt and Dirk Graudenz. General Assymetric Neural Networks and Structure Design by Genetic Algorithms. *Neural Networks*, 5(2):327–334, 1992. DESSY 91-046, Deutsches Electronen-Synchrotron, Hamburg, Germany, MAY 1991.

[BG93] Stephan Bornholdt and Dirk Graudenz. General Assymetric Neural Networks and Structure Design by Genetic Algorithms: A Learning Rule for Temporal Patterns. Hd-thep-93-26 lbl-34384, Lawrence Berkeley Laboratory, University of California, Berkeley, CA, July 1993.

[BK87] Aviv Bergman and Michel Kerszberg. Breeding Intelligent Automata. In *Proceedings of IEEE Conference on Neural Networks*, volume II, pages 63–70, San Diego, CA, June 21-24 1987.

[BM89] Richard K. Belew and John McInerney. Using the Genetic Algorithm to Wire Feed-forward Networks. Technical abstract, University of California, San Diego, La Jolla, CA, May 1989. Submitted to Neural Information Processing Systems 1989.

[BMS90] Richard K. Belew, John McInerney, and Nicol N. Schraudolph. Evolving Networks: Using Genetic Algorithms with Connectionist Learning. Cse technical report cs90-174, University of California at San Diego, La Jolla, CA, June 1990.

[Buk92] I. L. Bukatova. Evolutionary Computer. *Proceedings of the RNNS/IEEE Symposium on Neuroinformatics and Neurocomputers.*, I:467–477, October 7-10 1992.

[BW93] H. Braun and J. Weisbrod. Evolving Neural Feedforward Networks. In R.F. Albrecht, C.R. Reeves, and N.C Steele, editors, *Proceedings of the International Conference on Artificial Neural Networks and Genetic Algorithms*, pages 25–32. Springer-Verlag, 1993.

[Cal88] W.H. Calvin. The Brain as a Darwin Machine. *Nature*, 330:33–43, 1988.

[Car91] Marcelo H. Carugo. Optimization of Parameters of a Neural Network, applied to Document Recognition, using Genetic Algorithms. Nat. lab. technical note no. 049/91, N.V. Philips, Eindhoven, The Netherlands, 1991.

[Cau90] Thomas P. Caudell. Parametric Connectivity: Feasibility of Learning in Constrained Weight Space. In *Proceedings of the International Joint Conference on Neural Networks*, volume I, pages 667–675, 1990.

[Cau91] Maureen Caudill. Evolutionary Neural Networks. *AI Expert*, pages 28–33, March 1991.

[CC93] C. H. Chu and C. R. Chow. A Genetic Algorithm Approach to Supervised Learning for Multilayered Networks. In *World Congress on Neural Networks*, pages IV744 – IV747, 1993.

[CD89] Thomas P. Caudell and Charles P. Dolan. Parametric Connectivity: Training of Constrained Networks using Genetic Algorithms. In *Proceedings of the Third International Conference on Genetic Algorithms*, pages 370–374, 1989.

[CDRG89] M. Compiani, Montanari D., Serra R., and Valastro G. Classifier Systems and Neural Networks. In Caianiello E.R., editor, *Parallel Architectures and Neural Networks*, pages 33–43. World Scientific Press, Singapore, 1989.

[Cha90] David J. Chalmers. The Evolution of Learning: An Experiment in Genetic Connectionism. In D.S. Touretsky, J.L. Elman, T.J Sejnowski, and G.E. Hinton, editors, *Proceedings of the 1990 Connectionist Summer School*, pages 81–90. Morgan Kaufmann, 1990.

[CJ90] R. Collins and D. Jefferson. An Artificial Neural Network Representation for Artificial Organisms. In *Proceedings of the Conference on Parallel Problem Solving from Nature*, pages 259–263, 1990.

[CL91] E. Chang and R. Lippmann. Using Genetic Algorithms to Improve Pattern Classification Performance. In *Neural Information Processing Systems – NIPS 3*, pages 797–803. Morgan Kaufmann, 1991.

[CW92] Qi Chen and W. A. Weigand. Neural Net Model of Batch Processes and Optimization Based on an Extended Genetic Algorithm. In *Proceedings of the International Joint Conferenc on Neural Networks*, pages IV–519 – IV–524, 1992.

[Dav88] Lawrence Davis. Mapping Classifier Systems into Neural Networks. In *Proceedings of the Workshop on Neural Information Processing Systems 1*, pages 49–56, 1988.

[Dav89a] Lawrence Davis. Adapting Operator Probabilities in Genetic Algorithms. In *Proceedings of the Third International Conference on Genetic Algorithms*, pages 61–69, 1989.

[Dav89b] Lawrence Davis. Mapping Neural Networks into Classifier Systems. In *Proceedings of the 3rd International Conference on Genetic Algorithms*, pages 375–378, 1989.

[DB92] E. DeRouin and J. Brown. Alternative Learning Methods for Training Neural Network Classifiers. *Proceedings of the SPIE - The International Society for Optical Engineering*, 1710, pt.1:II–474–II–483, 1992.

[DD87a] Charles P. Dolan and Michael G. Dyer. Symbolic Schemata in Connectionist Memories: Role Binding and the Evolution of Structure. Technical report ucla-ai-87-11, AI Laboratory, University of California, Los Angeles, 1987.

[DD87b] Charles P. Dolan and Michael G. Dyer. Toward the Evolution of Symbols. In John J. Grefenstette, editor, *Proceedings of the Second International Conference on Genetic Algorithms*, pages 123–131, Hillsdale, New Jersey, 1987. Lawrence Erlbaum Associates.

[DDWA92] S. Dominic, R. Das, D. Whitley, and C. Anderson. Genetic Reinforcement Learning for Neural Networks. In *Proceedings of the International Joint Conference on Neural Networks*, pages II–71 – II–76, 1992.

[Des92] P.E. Dessert. Anomaly Detection in Data Using Neural Networks With natural selection. *Proceedings of the SPIE - The International Society for Optical Engineering*, 1710, pt.1:II–725–II–733, 1992.

[dG89] Hugo de Garis. WALKER, A Genetically Programmed, Time Dependent, Neural Net Which Teaches a Pair of Sticks to Walk. Technical report, Center for AI, George Mason Univ, Virginia, 1989.

[dG90a] Hugo de Garis. BRAIN Building with GenNets. *Proceedings of INNC-90*, 2:1036–1039, 1990.

[dG90b] Hugo de Garis. *Genetic Programming: Building Nanobrains with Genetically Programmed Neural Network Modules.* CADEPS AI Research Unit, Universitye Libre de Bruxelles, CP 194/7, B-1050 Brussels, Belgium, 1990.

[dG90c] Hugo de Garis. Genetic Programming: Evolution of a Time Dependent Neural Network Module which Teaches a Pair of Stick Legs to Walk. In *Proceedings of the 9th European Conference on Artificial Intelligence*, pages 204–206, Stockholm, Sweden, AUG 6-10 1990.

[dG92a] Hugo de Garis. Exploring GenNet Behaviors Using Genetic Programming to Explore Qualitatively New Behaviors in Recurrent Neural Networks. In *Proceedings of the International Joint Conference on Neural Networks*, pages III–547 – III–552. IJCNN-92, 1992.

[dG92b] Hugo de Garis. Steerable GenNets: the Genetic Programming of Steerable Behaviors in GenNets. In F.J. Varela and P. Bourgine, editors, *Toward a Practice of Autonomous Systems. Proceedings of the First European Conference on Artificial Life*, Cambridge, MA, USA, 1992. MIT Press.

[dG93a] Hugo de Garis. Circuits of Production Rule GenNets. The Genetic Programming of Artificial Nervous Systems. In *Artificial Neural Nets and Genetic Algorithms*, pages 699–705. ANNGA93, 1993.

[dG93b] Hugo de Garis. Incremental Evolution of Neural Networks: Genetic Programming in Incremental Steps. In *Proceedings of the World Congress on Neural Networks*, pages II447 – II450. WCNN93, 1993.

[DK87] W. B. Dress and J. R. Knisley. A Darwinian Approach to Artificial Neural Systems. In *1987 IEEE Conference on Systems, Man, and Cybernetics*, Oct 1987.

[dlB93] P. de la Brassinne. Genetic Algorithms and Learning of Neural Networks. *Bulletin Scientifique de l'Association des Ingenieurs Electriciens sortis de l'Institut Electrotechnique Montefiore*, 106(1):41–,58, 1993.

[DM92] Dipankar Dasgupta and Douglas McGregor. Designing Application-Specific Neural Networks using the Structured Genetic Algorithm. In *Proceedings of the International Conference on Combinations of Genetic Algorithms and Neural Networks*, pages 87–96, 1992.

[DMM91] N. Dodd, D. Macfarlane, and C. Marland. Optimization of Artificial Neural Network Structure Using Genetic Techniques Implemented on Multiple Transputers. In *Proceedings of Transputing '91*, 1991.

[Dod91] N. Dodd. Optimization of Network Structure using Genetic Techniques. In G. Rzevski and R. A. Adey, editors, *Applications of Artificial Intelligence in Engineering VI*. 1991.

[Dre87] W. B. Dress. Darwinian Optimization of Synthetic Neural Systems. In *Proceeding of the IEEE First Annual International Conference on Neural Networks*, 1987.

[Dre89] W. B. Dress. Genetic Optimization in Synthetic Systems. 1989.

[Dre90a] W. B. Dress. *Electronic Life and Synthetic Intelligent Systems*. Instrumentation and Controls Division, Oak Ridge Natuional Laboratory, 1990.

[Dre90b] W. B. Dress. In-Silico Gene Expression: A Specific Example and Possible Generalizations. In *Proceedings of Emergence and Evolution of Life-Forms*, 1990.

[DW92] Rajarshi Das and Darrell Whitley. Genetic Sparse Distributed Memories. In *Proceedings of the Conference on Combinations of Genetic Algorithms and Neural Networks*, pages 97–107, 1992.

[Ebe92] Russell C. Eberhart. The Role of Genetic Algorithms in Neural Network Query-Based Learning and Explanation Facilities. In *Proceedings of the Conference on Combinations of Genetic Algorithms and Neural Networks*, pages 169–183, 1992.

[ED91] R. C. Eberhart and R. W. Dobbins. Designing Neural Network Explanation Facilities Using Genetic Algorithms. In *Proceedings of the International Joint Conference on Neural Networks*, pages 1758–1763, 1991.

[Eli92a] J.G. Elias. Target tracking using impulsive analog circuits. *Proceedings of the SPIE - The International Society for Optical Engineering*, 1709, pt.1:338–350, 1992.

[Eli92b] John G. Elias. Genetic Generation of Connection Patterns for a Dynamic Artificial Neural Network. In *Proceedings of the Conference on Combinations of Genetic Algorithms and Neural Networks*, pages 38–54, 1992.

[FA93] D. Fielder and C.O. Alford. Counting and Naming Connection Islands on a Grid of Conductors. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Proceedings of the Conference on Artificial Neural Networks and Genetic Algorithms*, page 731. ANNGA93, Springer-Verlag, 1993.

[Fal91] J.F. Falcon. Simulated Evolution of Modular Networks. In A. Prieto, editor, *Artificial Neural Networks, IWANN91, Granada*, pages 204–211. Lecture notes in Computer Science 540, Springer Verlag, 1991.

[Fel93] David S. Feldman. Fuzzy Network Synthesis and Genetic Algorithms. In *Proceedings of the Fifth International Conference on Genetic Algorithms*, 1993.

[FF93] David B. Fogel and Lawrence J. Fogel. Method and Apparatus for Training a Neural Network Using Evolutionary Programming. Patent 5214746, United States, 25 MAY 1993.

[FFP90] D.B. Fogel, L.J. Fogel, and V.W. Porto. Evolving Neural Networks. *Biological Cybernetics*, 63:487–493, 1990.

[FH93] B. Freisleben and Härtfelder. Optimization of Genetic Algorithms by Genetic Algorithms. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 392–399. Springer-Verlag, 1993.

[FHG93] A.A. Fekadu, E.L. Hines, and J.W. Gardner. Genetic Algorithm Design of Neural Net Based Electronic Nose. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Networks and Genetic Algorithms*, pages 691–698. Springer-Verlag, 1993.

[FJ86] A. J Fenanzo Jr. Darwinian Evolution as a Paradigm for AI Research. *SIGART Newsletter*, (97):22–23, July 1986.

[Flo92] D. Floreano. Patterns of Interactions in Ecosystems of Neural Networks. Master's thesis, Neural Computation, Dept of Comp Sci., Univ of Stirling, 1992.

[Flo93] D. Floreano. ROBOGEN: a Software Package for Evolutionary Control Systems. Technical Report 93-01, Cognitive technology laboratory, Trieste, 1993.

[FM91] J.F. Fontanari and R. Meir. Evolving a Learning Algorithm for the Binary Perceptron. *Network*, 2:353–359, 1991.

[FM92] B. Fullmer and R. Miikkulainen. Using Marker-Based Genetic Encoding of Neural Networks to Evolve Finite-State Behaviour. In F.J. Varela and P. Bourgine, editors, *Toward a Practice of Autonomous Systems. Proceedings of the First European Conference on Artificial Life*, Cambridge, MA, USA, 1992. MIT Press.

[FM94] D. Floreano and F. Mondada. Automatic Creation of an Autonomous Agent: Genetic Evolution of a Neural-Network Driven Robot. In *Proceedings of the Conference on Simulation of Adaptive Behavior*, 1994.

[FMP91] D. Floreano, O. Miglino, and D. Parisi. Emerging Complex Behaviours in Ecosystems of Neural Networks. 1991.

[Fog93a] David B. Fogel. Using Evolutionary Programming to Create Neural Networks that are Capable of Playing Tic-Tac-Toe. In *Proceedings of the American Power Conference*, pages 875–879. IEEE, 1993.

[Fog93b] David B. Fogel. Using Evolutionary Programming to Create Neural Networks that are Capable of Playing Tic-Tac-Toe. In *Proceedings of the International Conference on Neural Networks*, 1993.

[For93] Stephanie Forrest, editor. *Proceedings of the Fifth International Conference on Genetic Algorithms*, San Mateo, CA, July 17-21 1993. University of Illinois at Urbana Champaign, Morgan Kaufmann.

[FPP86] D. J. Farmer, N. H. Packard, and A. S. Perelson. The immune system, adaptation, and machine learning. *Physica*, 22D:187–204, 1986.

[Fri93] Bernd Fritzke. Growing Cell Structures – A Self-Organizing Network for Unsupervised and Supervised Learning. Technical Report TR-93-026, International Computer Science Institute, 1947 Center Street, Suit 600, Berkeley, California 94704, may 1993.

[FS93] D.B. Fogel and P.K. Simpson. Evolving Fuzzy Clusters. In *Proceedings of the International Conference on Neural Networks*. ICNN93, 1993.

[GB92] J. C. Gallagher and R. D Beer. A Qualitative Dynamical Analysis of Evolved Locomotion Control. In H. Roitblat, J-A. Meyer, and S. Wilson, editors, *From Animals to Animats, Proceedings of the Second International Conference on Simuation of Adaptive Behaviour (SAB 92)*. The MIT Press, Cambridge, MA, 1992.

[GHS92] Aloke Guha, Steven A. Harp, and Tariq Samad. Genetic Algorithm Synthesis of Neural Networks. Patent 5140530, United States, 18 AUG 1992.

[Gie88] A. Gierer. Spatial Organization and Genetic Information in Brain Development. *Biological Cybernetics*, 59:13–21, 1988.

[GJ93] G. W. Game and C. D. James. The Application of Genetic Algorithms to the Optimal Selection of Parameter Values in Neural Networks for Attitude Control Systems. In *IEE Colloquium on 'High Accuracy Platform Control in Space'*, volume Digest No. 1993/148, pages 3/1–3/3. IEE, London, 1993.

[G.M87] Edelman G.M. *Neural Darwinism: The Theory of Neuronal Group Selection.* Basic Books, New York, 1987.

[Gre85] John J. Grefenstette, editor. *Proceedings of the First International Conference on Genetic Algorithms and their Applications*, Pittsburgh, Pa, July 24-26 1985. Lawrence Erlbaum Associates.

[Gre87] John J. Grefenstette, editor. *Proceedings of the Second International Conference on Genetic Algorithms and their Applications*, Hillsdale, New Jersey, July 28-31 1987. Massachusetts Institute of Technology, Cambridge, MA, Lawrence Erlbaum Associates.

[Gru92a] Frederic Gruau. Cellular Encoding of Genetic Neural Network. Research report 92.21, Laboratoire de l'Informatique du Parallélisme, Ecole Normale Supérieure de Lyon, 1992.

[Gru92b] Frederic Gruau. Cellular Encoding of Genetic Neural Networks I. Theoretical Properties. submitted to evolutionnary computation, 1992.

[Gru92c] Frederic Gruau. Genetic Synthesis of Boolean Neural Networks with a Cell Rewriting Developmental Process. In L.D. Whitley and J.D. Schaffer, editors, *Proceedings of COGANN-92 International Workshop on Combinations of Genetic Algorithms and Neural Networks*, pages 55–74. IEEE Computer Society Press, 1992.

[Gru93a] Frederic Gruau. Genetic Synthesis of Modular Neural Networks. In *Proceedings of the Fifth International Conference on Genetic Algorithms*, 1993.

[Gru93b] Frederic Gruau. A Learning and Pruning Algorithm for Genetic Neural Networks. In *European Symposium on Artificial Neural Networks*, 1993.

[Gru93c] Fredric Gruau. Cellular Encoding as a Graph Grammar. *IEE Colloquium on Grammatical Inference: Theory, Applications and Alternatives*, (Digest No.092):17/1–10, 22-23 April 1993.

[Gru94a] Frederic Gruau. Genetic Micro Programming of Neural Networks. In Kim Kinnear, editor, *Advances in Genetic Programming*. MIT Press, 1994.

[Gru94b] Frederic Gruau. *Neural Network Synthesis Using Cellular Encoding and the Genetic Algorithm.* PhD thesis, PhD Thesis, Ecole Normale Supérieure de Lyon, 1994. anonymous ftp: lip.ens-lyon.fr (140.77.1.11) directory pub/Rapports/PhD file PhD94-01-E.ps.Z (english) PhD94-01-F.ps.Z (french).

[GS92] Jose Gonzalez-Seco. A Genetic Algorithm as the Learning Procedure for Neural Networks. In *Proceedings of the International Joint Conference on Neural Networks*, pages I–835 – I–840. IJCNN-92, 1992.

[GU92] Zhichao Guo and Robert Uhrig. Using Genetic Algorithms to Select Inputs for Neural Networks. In *Proceedings of the Workshop on Combinations of Genetic Algorithms and Neural Networks*, pages 223–234. COGANN92, 1992.

[GW93a] Frederic Gruau and Darrell Whitley. Adding Learning to the Cellular Developmental Process: a Comparative Study. *Evolutionary Computation*, 1(3), 1993.

[GW93b] Frederic Gruau and Darrell Whitley. Adding Learning to the Cellular Developmental Process: a Comparative Study. Research report rr93-04, Laboratoire de l'Informatique du Parallélisme, Ecole Normale Supérieure de Lyon, 1993.

[GW93c] Frederic Gruau and Darrell Whitley. The Cellular Development of Neural Networks: the Interaction of Learning and Evolution. Technical Report 93-04, Laboratoire de l'Informatique du Parallelisme, Ecole Normal Superieure de Lyon, 1993.

[Han89] P. J. B. Hancock. Optimising Parameters in Neural Net Simulations by Genetic Algorithm. In *Mini-Symposium on Neural Network Computation*. Rank Prize Funds, Broadway: unpublished, 1989.

[Han90] P. J. B. Hancock. GANNET: Design of a Neural Network for Face Recognition by Genetic Algorithm. In *Proceedings of the IEEE Workshop on Genetic Algorithms, Simulated Annealing and Neural Networks*, University of Glasgow, Scotland, 1990.

[Han92a] P. J. B. Hancock. *Coding Strategies for Genetic Algorithms and Neural Nets*. PhD thesis, Department of Computing Science and Mathematics, University of Stirling, 1992.

[Han92b] P. J. B. Hancock. Genetic Algorithms and Permutation Problems: a Comparison of Recombination Operators for Neural Net Structure Specification. In D. Whitley, editor, *Proceedings of COGANN workshop, IJCNN, Baltimore*. IEEE, 1992.

[Han92c] P. J. B. Hancock. Pruning Neural Nets by Genetic Algorithm. In I. Aleksander and J.G. Taylor, editors, *Proceedings of the International Conference on Artificial Neural Networks, Brighton*, pages 991–994. Elsevier, 1992.

[Han92d] P. J. B. Hancock. Recombination Operators for the Design of Neural Nets by Genetic Algorithms. In R. Männer and B. Manderick, editors, *Parallel Problem Solving from Nature 2*, pages 441–450. Elsevier, North Holland, 1992.

[Hei89] J. Heistermann. Parallel Algorithms for Learning in Neural Networks with Evolution Strategy. *Parallel Computing*, 12, 1989.

[Hei90] J. Heistermann. Learning in Neural Nets by Genetic Algorithms. In R. Eckmiller, G. Hartmann, and G. Hauske, editors, *Parallel Processing in Neural Systems and Computers*, pages 165–168. Elsevier Science Publishers, 1990.

[Hei91] J Heistermann. The Application of a Genetic Approach as an Algorithm for Neural Networks. In H-P. Schwefel and R. Männer, editors, *Parallel Problem Solving from Nature*, pages 297–301. Lecture notes in Computer Science 496, Springer Verlag, 1991.

[Hei92] J. Heistermann. A Mixed Genetic Approach to the Optimization of Neural Controllers. In P. Dewilde and J. Vandewalle, editors, *CompEuro 1992 Proceedings. Computer Systems and Software Engineering*, pages 459–464, Los Alamitos, CA, USA, 1992. IEEE Comput. Soc. Press.

[HF92] A.W. Ho and G.C. Fox. Competitive-Cooperative System of Distributed Artificial Neural Agents. In P. Messina and A. Murli, editors, *Parallel Computing: Problems, Methods and Applications. Selection of Papers Presented at the Conference on Parallel Computing: Achievements, Problems and Prospects*, pages 499–507. Elsevier, Amsterdam, Netherlands, 1992.

[HHB90] R. G. Hoptroff, T. J. Hall, and R. E. Burge. Experiments With a Neural Controller. In *1990 International Joint Conference on Neural Networks - IJCNN 90*, volume 2, pages 735–740. IEEE, New York, 1990.

[HHC92] P. Husbands, I. Harvey, and D. T. Cliff. Analysing Recurrent Dynamical Networks Evolved for Robot Control. Technical Report CSRP265, University of Sussex, School of Cognitive and Computing Sciences, 1992.

[HHC93] I. Harvey, P. Husbands, and D. Cliff. Genetic Convergence in a Species of Evolved Robot Control Architectures. Technical Report CSRP 267, Cognitive Science, university of Sussex, 1993.

[HN87] Geoffrey E. Hinton and Stephen J. Nowlan. How Learning Can Guide Evolution. *Complex Systems*, 1(1):495–502, JUN 1987.

[HS90] K.J. Hintz and J.J. Spofford. Evolving a Neural Network. In A. Meystel, editor, *Proceedings of the 5th IEEE International Symposium on Intelligent Control*, pages 479–484, Los Alamitos, CA, SEPT 1990. IEEE Computer Society Press.

[HS91a] P. J. B. Hancock and L. S Smith. GANNET: Genetic Design of a Neural Net for Face Recognition. In H-P. Schwefel and R. Männer, editors, *Proceedings of the Conference on Parallel Problem Solving from Nature*, pages 292–296. Lecture notes in Computer Science 496, Springer Verlag, 1991.

[HS91b] Steven Harp and Tariq Samad. Genetic Synthesis of Neural Network Architecture. In L. Davis, editor, *Handbook of Genetic Algorithms*, pages 202–221. Van Nostrand Reinhold, 1991.

[HS91c] Steven Alex Harp and Tariq Samad. Genetic Optimization of Self-Organizing Feature Maps. In *Proceedings of the International Joint Conference on Neural Networks*, volume I, pages 341–346, 1991.

[HS92a] Steven A. Harp and Tariq Samad. Optimizing Neural Networks with Genetic Algorithms. *Proceedings of the American Power Conference*, 54 pt 2:1138–1143, 1992.

[HS92b] O.E. Holland and M.A. Snaith. Neural Control of Locomotion in a Quadrupedal Robot. *IEE Proceedings Part F: Radar and Signal Processing*, 139(6):431–436, DEC 1992.

[HS93] Mohamad H. Hassoun and Jing Song. Multilayer Perceptron Learning Via Genetic Search for Hidden Layer Activations. In *Proceedings of the World Congress on Neural Networks*, pages III437 – III444. WCNN93, 1993.

[HSA89] S. A. Harp, T. Samad, and Guha A. The Genetic Synthesis of Neural Networks. Technical Report TR CSDD-89-I4852-2, Honeywell CSDD, 1989.

[HSG89a] S. A. Harp, T. Samad, and A. Guha. Designing Application-Specific Neural Networks Using the Genetic Algorithm. In D.S. Touretzky, editor, *Neural Information Processing Systems 2*, 1989.

[HSG89b] S. A. Harp, T. Samad, and A. Guha. Towards the Genetic Synthesis of Neural Networks. In J.D. Schaffer, editor, *Proceedings of the Third International Conference on Genetic Algorithms*, pages 360–369. Morgan Kaufmann, 1989.

[HSU91] K-U. Hőffgen, H.P. Siemon, and A Ultsch. Genetic Improvement of Feedforward Nets for Approximating Functions. In H-P. Schwefel and R. Mănner, editors, *Proceedings of the Conference on Parallel Problem Solving from Nature*, pages 302–306. Lecture notes in Computer Science 496, Springer Verlag, 1991.

[HU89a] V. Honavar and L. Uhr. Brain-Structured Networks That Perceive and Learn. *Connection Science*, 1:139–159, 1989.

[HU89b] V. Honavar and L. Uhr. Generation, Local Receptive Fields, and Global Convergence Improve Perceptual Learning in Connectionist Networks. In *Proceedings of the Tenth International Joint Conference on Artificial Intelligence*. Morgan Kaufmann, Palo Alto, 1989.

[HU89c] V. Honavar and L. Uhr. A Network of Neuron-Like Units That Learns by Generation As Well As Reweighting of its Links. In *Proceedings of the 1988 Connectionist Models Summer School*. Morgan Kaufmann, Palo Alto, 1989.

[HU93] V. Honavar and L. Uhr. Generative Learning Structures and Processes for Generalized Connectionist Networks. *Information Sciences*, 70:75–108, 1993.

[Hua92] R. Huang. Systems Control With the Genetic Algorithm and the Nearest Neighbour Classification. *CC-AI*, 9(2-3):225–236, 1992.

[HW92] L.S. Hsu and Z.B. Wu. Input Pattern Encoding Through Generalized Adaptive Search. In L.D. Whitley and J.D. Schaffer, editors, *Proceedings of COGANN-92 International Workshop on Combinations of Genetic Algorithms and Neural Networks*, pages 235–247. IEEE Computer Society Press, 1992.

[Ich90] Y. Ichikawa. Evolution of Neural Networks and Application to Motion Control. In *Proceedings of the IEEE International Conference on Intelligent Motion Control*, pages 239–245. IEEE, 1990.

[JCC+90] D. Jefferson, R. Collins, C. Cooper, M. Dyer, M. Flowers, R. Korf, C. Taylor, and A. Wang. Evolution as a Theme in Artificial Life: the Genesys/Tracker System. Technical Report UCLA-AI-90-09, Computer Science, UCLA, 1990.

[JF92] D.J. Janson and J.F. Frenzel. Application of Genetic Algorithms to the Training of Higher Order Neural Networks. *Journal of Systems Engineering*, 2(4):272–276, 1992.

[JM93] A.J. Jones and D. MacFarlane. Comparing Networks With Differing Neural-Node Functions Using Transputer-Based Genetic Algorithms. *Neural Computing and Applications*, 1:256–267, 1993.

[Jon93] A.J. Jones. Genetic Algorithms and Their Applications to the Design of Neural Networks. *Neural Computing and Applications*, 1:32–45, 1993.

[JR93] C. Jacob and J. Rehder. Evolution of Neural Net Architectures by a Hierachical Grammar-Based Genetic System. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 72–79. Springer-Verlag, 1993.

[KB86] Michel Kerszberg and Aviv Bergman. The Evolution of Data Processing Abilities in Competing Automata. In R.M.J Cotterill, editor, *Computer Simulation in Brain Science, Copenhagen, Denmark*, pages 249–259l. Cambridge University Press, August 1986.

[KC86] K.G. Kirby and Michael Conrad. Intraneuronal Dynamics as a Substrate for Evolutionary Learning. *Physica D*, 22:205–215, 1986.

[KCK89] K.G. Kirby, Michael Conrad, and R.R. Kampfner. Evolutionary Learning in Reaction-Diffusion Neurons. SUBMITTED TO Bull. Math. Biol., 1989.

[KDW92] N. Karunanithi, R. Das, and D. Whitley. Genetic Cascade Learning for Neural Networks. In L.D. Whitley and J.D. Schaffer, editors, *Proceedings of COGANN-92 International Workshop on Combinations of Genetic Algorithms and Neural Networks*, pages 134–145. IEEE Computer Society Press, 1992.

[Ker] Michel Kerszberg. *Genetic and Epigenetic Factors in Neural Circuit Wiring (preliminary)*. Institut fur Festkorperforschung der.

[KIH92] M. Kouchi, H. Inayoshi, and T. Hoshino. Optimization of Neural-Net Structure by Genetic Algorithm with Diploidy and Geographical Isolation Model.

Journal of Japanese Society for Artificial Intelligence, 7(3):509–517, May 1992.

[Kir88] K.G. Kirby. *Intraneuronal Dynamics and Evolutionary Learning.* PhD thesis, Dept. of Computer Science, Wayne State University, 1988.

[Kit90a] Hiroaki Kitano. Designing Neural Network Using Genetic Algorithm with Graph Generation System. *Complex Systems*, 4:461–476, 1990.

[Kit90b] Hiroaki Kitano. Empirical Studies on the Speed of Convergence of Neural Network Training Using Genetic Algorithms. In *Proceedings of the 8th National Conference on Artificial Intelligence (AAAI-90)*, pages 789–795. PROC AAAI-90, MIT Press, Cambridge, 1990.

[Kit92] Hiroaki Kitano. Neurogenetic Learning: An Integrated Method of Designing and Training Neural Networks using Genetic Algorithms. Cmu-cmt-92-134, Carnegie Mellon University, MAR 1992.

[Kit93] Hiroaki Kitano. Continuous Generation Genetic Algorithms. *Journal of the Society of Instrument and Control Engineers*, 32(1):31–8, Jan. 1993.

[KN90] Nagesh Kadaba and Kendall E. Nygard. *Improving the Performance of Genetic Algorithms in Automated Discovery of Parameters.* Dept. of SC and OR, North Dakota State University, JAN 25 1990. Draft.

[Koz92] John R. Koza. *Genetic Programming: On the Programming of Computers by Means of Natural Selection.* MIT Press, Cambridge, Mass., 1992.

[KR91] John R. Koza and James P. Rice. Genetic Generation of Both the Weights and Architecture for a Neural Network. In *Proceedings of the International Joint Conference on Neural Networks*, volume II, pages 397–404. IJCNN-91, 1991.

[KR92] M.N. Karim and S.L. Rivera. Use of Recurrent Neural Networks for Bioprocess Identification in On-Line Optimization by Micro-Genetic Algorithms. *Proceedings of the American Control Conference*, 3:1931–1932, 1992.

[Kri92] K. Krishnakumar. Immunized Neurocontrol - Concepts and Initial Results. In L.D. Whitley and J.D. Schaffer, editors, *Proceedings of COGANN-92 International Workshop on Combinations of Genetic Algorithms and Neural Networks*, pages 146–168. IEEE Computer Society Press, 1992.

[KS86] S.A. Kauffman and R.G. Smith. Adaptive Automata Based on Darwinian Selection. *Physica D*, 22:68–82, 1986.

[KS91a] Hillol Kargupta and Robert E. Smith. System Identification with Evolving Polynomial Networks. In *Proceedings of the Fourth International Conference on Genetic Algorithms*, pages 370–376, 1991.

[KS91b] R. Keesing and D.G. Stork. Evolution and Learning in Neural Networks, the Number and Distribution of Learning Trials Affect the Rate of Evolution. In R.P. Lippmann, J.E. Moody, and D.S Touretzky, editors, *Advances in Neural Information Processing Systems 3*, pages 804–810. Morgan Kaufmann, 1991.

[KS93] L. Kwiatkowski and J.P. Stromboni. Neuromimetic Algorithm processing: Tools for Design of Dedicated Architectures. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 706–711. Springer-Verlag, 1993.

[LA91] Michael L. Littman and David H. Ackley. Adaptation in Constant Utility Non-Stationary Environments. In *Proceedings of the Fourth International Conference on Genetic Algorithms*, pages 136–142, 1991.

[Lan89] Christopher G. Langton, editor. *Artificial Life: the Proceedings of an Interdisciplinary Workshop on the Synthesis and Simulation of Living Systems*, Redwood City, CA, September 1989. Addison-Wesley. Workshop held September, 1987 in Los Alamos, New Mexico.

[Lan93] Frank Lange. "Uber den Zusammenhang zwischen Komplexit"at und Generalisierungsf"ahigkeit Neuronaler Netze. Diplomarbeit, Universit"at Karlsruhe, Institut f"ur Logik, Komplexit"at und Deduktionssysteme, 1993. Beyond Soft-Weight-Sharing: Soft-Entropy-Minimization.

[Lan94] Christopher G. Langton, editor. *Artificial Life III: Proceedings of the Workshop on Artificial Life*, Reading, MA, 1994. Addison-Wesley. Workshop held June, 1992 in Santa Fe, New Mexico.

[LC92] W.K. Lai and G.G. Coghill. Genetic Breeding of Control Parameters for the Hopfield/Tank Neural Net. In *Proceedings of the International Joint Conference on Neural Networks*, pages IV–618 – IV–623. IJCNN-92, 1992.

[LFS92] M. Anthony Lewis, Andrew H. Fagg, and Alan Solidum. Genetic Programming Approach to the Construction of a Neural Network for Control of a Walking Robot. In *Proceedings of IEEE International Conference on Robotics and Automation*, volume 3, pages 2618–2623, Piscataway, NJ, USA, 1992. IEEE.

[LNNR92] K. Lindgren, A. Nilsson, M.G. Nordahl, and I. R ade. Regular Language Inference Using Evolving Neural Networks. In L.D. Whitley and J.D. Schaffer, editors, *Proceedings of COGANN-92 International Workshop on Com-*

binations of Genetic Algorithms and Neural Networks, pages 75–86. IEEE Computer Society Press, 1992.

[LNNR93] K. Lindgren, A. Nilsson, M.G. Nordahl, and I. R ade. Evolving Recurrent Neural Networks. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 55–62. Springer-Verlag, 1993.

[LTFR92] Christopher G. Langton, Charles Taylor, J. Doyne Farmer, and Steen Rasmussen, editors. *Artificial Life II: Proceedings of the Workshop on Artificial Life*, Redwood City, Calif., 1992. Addison-Wesley. Workshop held February, 1990 in Santa Fe, New Mexico.

[LW87] S. Lehar and J. Weaver. A Developmental Approach to Neural Network Design. In *Proceedings of the IEEE International Conference on Neural Networks*, pages 97–104. IEEE Press, 1987.

[Man93a] M. Mandischer. Representation and Evolution of Neural Networks. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms Proceedings of the International Conference at Innsbruck, Austria*, pages 643–649. Springer, Wien and New York, 1993.

[Man93b] V. Maniezzo. Searching Among Search Spaces: Hastening the Genetic Evolution of Feedforward Neural Networks. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 635–643. Springer-Verlag, 1993.

[Man94] V. Maniezzo. Genetic Evolution of the Topology and Weight Distribution of Neural Networks. *IEEE Transactions on Neural Networks*, 5:39–53, 1994.

[Mar92a] Leonardo Martí. Genetically Generated Neural Networks I: Representational Effects. In *Proceedings of the International Joint Conference on Neural Networks*, pages IV–537 – IV–542. IJCNN-92, 1992.

[Mar92b] Leonardo Martí. Genetically Generated Neural Networks II: Searching for an Optimal Representation. In *Proceedings of the International Joint Conference on Neural Networks*, pages II–221 – II–226, 1992.

[May93] Erik Mayer. Genetic Algorithm Approach to Neural Network Optimization. Masters thesis, University of Toledo, Toledo, Ohio, August 1993.

[MB94a] F. Menczer and R.K. Belew. Evolving Sensors in Environments of Controlled Complexity. In R. Brooks and P. Maes, editors, *Artificial Life IV*, Cambridge, MA, 1994. MIT Press.

[MB94b] F. Menczer and R.K. Belew. Latent Energy Environments. In R.K. Belew and M. Mitchell, editors, *Plastic Individuals in Evolving Populations*, Santa Fe Institute Studies in the Sciences of Complexity. Addison Wesley, Reading, MA, 1994. (in press).

[MBL93] R.J. Mitchell, J.M. Bishop, and W. Low. Using a Genetic Algorithm to Find the Rules of a Neural Network. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 664–669. Springer-Verlag, 1993.

[MD] Michael McInerney and Atam P. Dhawan. Use of Genetic Algorithms with Back Propagation in Training of Feed-Forward Neural Networks. preprint from the Author; don't "no" about publication.

[MD89] D.J. Montana and L. Davis. Training Feedforward Neural Networks Using Genetic Algorithms. In *Proceedings of the Eleventh International Joint Conference on Artificial Intelligence*, pages 762–767. San Mateo, CA: Morgan Kaufmann., 1989.

[MdR92] Ricardo Jose Machado and Armando Freitas da Rocha. *Evolutive Fuzzy Neural Networks*. IEEE, Piscataway, NJ, 1992.

[MF93] M. Mitchell and S. Forrest. Genetic Algorithms and Artificial Life. *Artificial Life*, 1993.

[M̋90] Heinz Műhlenbein. Limitations of Multi-Layer Perceptron Networks - Steps Towards Genetic Neural Networks. *Parallel Computing*, 14:249–260, 1990.

[M̋92] Heinz Műhlenbein. Parallel Genetic Algorithms and Neural Networks as Learning Machines. In D. J. Evans, G. R. Joubert, and H. Liddell, editors, *Parallel computing '91 Proceedings of the International Conference*, pages 91–103, Amsterdam, 1992. North-Holland Publishing Co.

[MK89] Heinz Műhlenbein and Jörg Kindermann. The Dynamics of Evolution and Learning: Towards Genetic Neural Networks. In R. Pfeifer, Z. Schreter, F. Fogelman-Soulie, and L. Steels, editors, *Connectionism in Perspective*, pages 173–197. Elsevier Science Publishers B.V. (North-Holland), 1989.

[MK92] Y. Maeda and Y. Kanata. A Genetic Algorithm for an Unsupervised Learning of Neural Networks. *Engineering & Technology*, 10(2):1–7, 1992.

[MM92] Reinhart Männer and Bernhard Manderick, editors. *Proceedings of the Second Conference on Parallel Problem Solving from Nature, Brussels, Belgium*, Amsterdam, September 28-30 1992. Elsevier.

[MM93] David E. Moriarty and Risto Miikkulainen. Evolving Complex Othello Strategies Using Marker-based Genetic Encoding of Neural Networks. Technical Report AI93-206, Department of Computer Sciences, The University of Texas at Austin, 1993.

[MM94a] David E. Moriarty and Risto Miikkulainen. Evolving Neural Networks to Focus Minimax Search. In *Proceedings of the Twelfth National Conference on Artificial Intelligence (AAAI-94)*, Seattle, WA, 1994.

[MM94b] David E. Moriarty and Risto Miikkulainen. Using Evolutionary Neural Networks for Value Ordering in Constraint Satisfaction Problems. Technical Report AI94-218, Deptartment of Computer Sciences, The University of Texas at Austin, 1994.

[MN90] Borut Maricic and Zoran Nikolov. GENNET - System for Computer Aided Neural Network Design Using Genetic Algorithms. In *Proceedings of the International Joint Conference on Neural Networks*, pages I–102 – I–105, Washington, DC, Jan 1990.

[MOD92] D. R. McGregor, M. O. Odetayo, and D. Dasgupta. Adaptive-Control of a Dynamic System Using Genetic-Based Methods. In *Proceedings of the 1992 IEEE International Symposium on Intelligent Control*, pages 521–525. IEEE, 1992.

[MP90] F. Menczer and D. Parisi. 'Sexual' Reproduction in Neural Networks. Technical Report PCIA-90-06, C.N.R.Rome, 1990.

[MP92a] F. Menczer and D. Parisi. Evidence of Hyperplanes in the Genetic Learning of Neural Networks. *Biological Cybernetics*, 66(3):283–289, 1992.

[MP92b] F. Menczer and D. Parisi. A Model for the Emergence of Sex in Evolving Networks: Adaptive Advantage or Random Drift? In F.J. Varela and P. Bourgine, editors, *Toward a Practice of Autonomous Systems. Proceedings of the First European Conference on Artificial Life*, pages 337–345, Cambridge, MA, USA, 1992. MIT Press.

[MP92c] F. Menczer and D. Parisi. Recombination and Unsupervised Learning: Effects of Crossover in the Genetic Optimization of Neural Networks. *Network: Computation in Neural Systems*, 3(4):423–442, Nov 1992.

[MPC+93] Merelo, Paton, Canias, Prieto, and Moran. Genetic Optimization of a Multilayer Neural Network for Cluster Classification Tasks. *Neural Network World*, pages 175–186, 1993.

[MPP93] O. Miglino, R. Pedone, and D. Parisi. A 'Noise Gene' for Econets. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 588–594. Springer-Verlag, 1993.

[MS86] E. Mjolsness and D. H. Sharp. A Preliminary Analysis of Recursively Generated Networks. In *Proceedings of the American Institute of Physics (Special Issue on Neural Nets)*, 1986.

[MS87] J. Maynard Smith. When Learning Guides Evolution. *Nature*, 329:761–762, 1987.

[MS93] F.J. Marin and F. Sandoval. Genetic Synthesis of Discrete-Time Recurrent Neural Network. *New Trends in Neural Computation, Springer-Verlag*, pages 179–184, 1993.

[MSA88a] Eric Mjolsness, David H. Sharp, and Bradley K. Alpert. *Genetic Parsimony in Neural Nets*. 1988.

[MSA88b] Eric Mjolsness, David H. Sharp, and Bradley K. Alpert. Scaling, Machine Learning, and Genetic Neural Nets. La-ur-88-142, Theoretical Division, Los Alamos National Laboratory, March 1988.

[MSA89] Eric Mjolsness, David H. Sharp, and Bradley K. Alpert. Scaling, Machine Learning, and Genetic Neural Nets. *Advances in Applied Mathematics*, 10, 1989.

[MTH89] G.F. Miller, P.M. Todd, and S.U. Hegde. Designing Neural Networks Using Genetic Algorithms. In J.D. Schaffer, editor, *Proceedings of the Third International Conference on Genetic Algorithms*, pages 379–384. Morgan Kaufmann, 1989.

[MTK93] S. Mikami, H. Tano, and Y. Kakazu. An Autonomous Legged Robot That Learns to Walk Through Simulated Evolution. In *Self-Organisation and Life, From Simple Rules to Global Complexity, Proceedings of the Second European Conference on Artificial Life*, pages 758–767. MIT Press, Cambridge, 1993.

[Mun93] P. Munro. Genetic Search for Optimal Representations in Neural Networks. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 628–634. Springer-Verlag, 1993.

[MW92] John R. McDonnell and Don E. Waagen. Evolving Neural Network Architecture. *Proceedings of SPIE - The International Society for Optical Engineering*, 1766:690–701, 1992.

[MW93a] John R. McDonnell and Don E. Waagen. Determining Neural Network Hidden Layer Size Using Evolutionary Programming. In *Proceedings of the*

World Congress on Neural Networks 93, pages III564 – III567. WCNN93, 1993.

[MW93b] John R. McDonnell and Don E. Waagen. Evolving Neural Network Connectivity. In *Proceedings of the American Power Conference*, pages 863–868. IEEE, 1993.

[MW94] John R. McDonnell and Don E. Waagen. Evolving Recurrent Perceptrons for Time-Series Modeling. *IEEE Transactions on Neural Networks*, 5:24–38, 1994.

[NAN92] T. Nagao, T. Agui, and H. Nagahashi. Structural Evolution of Neural Networks by a Genetic Method. *Transactions of the Institute of Electronics, Information and Communication Engineers D-II*, J75D-II(9):1634–1637, Sep 1992.

[NAN93a] T. Nagao, T. Agui, and H. Nagahashi. A Genetic Method for Optimization of Asynchronous Random Neural Networks and its Application to Action Control. In *IJCNN'93-NAGOYA Proceedings of the 1993 International Joint Conference on Neural Networks, Nagoya (Japan)*, pages 2869–2872. IEEE, 1993.

[NAN93b] T. Nagao, T. Agui, and H. Nagahashi. Structural Evolution of Neural Networks Having Arbitrary Connection by a Genetic Method. E76-D(6):689–697, 1993.

[NEP90] S. Nolfi, J.L. Elman, and D. Parisi. Learning and Evolution in Neural Networks. Technical Report CRL TR 9019, UCSD, July 1990.

[NL93] M.N. Narayanan and S.B. Lucas. A Genetic Algorithm to Improve a Neural Network to Predict a Patient's Response to Warfarin. *Methods of Information in Medicine*, 32(1):55–8, 1993.

[NP91a] S. Nolfi and D. Parisi. Auto-Teaching Networks That Develop Their Own Teaching Input. Technical Report PCIA-91-03, Dept. of Cognitive Processes and Artificial Intelligence, 1991.

[NP91b] S. Nolfi and D. Parisi. Growing Neural Networks. Technical Report PCIA-91-15, Institute of Psychology, CNR, Rome, 1991. Also in Proceedings of ALIFE III, 1992.

[NP93] S. Nolfi and D. Parisi. Self-Selection of Input Stimuli for Improving Performance. In G.A. Bekey and K.Y. Goldberg, editors, *Neural Networks In Robotics*, pages 403–420. Kluwer academic publishers, 1993.

[OFM92] S. Oliker, M. Furst, and O. Maimon. A Distributed Genetic Algorithm for Neural Network Design and Training. *Complex Systems*, 6(5):459–477, Oct 1992.

[OKJ+91] Setsuo Ohsuga, Hannu Kangassalo, Hannu Jaakkola, Koichi Hori, and N. Yonezaki. Information Modeling and Knowledge Bases: Foundations, Theory, and Applications. IOS Press, Amsterdam, 1991.

[O'N92] A.W. O'Neill. Genetic Based Training of Two-Layer, Optoelectronic Neural Network. *Electronics Letters*, 28(1):47–48, Jan 1992.

[Oos89] G.D. Oosthuizen. Machine Learning: A Mathematical Framework for Neural Network, Symbolic and Genetic-Based Learning. In *Proceedings of the Third International Conference on Genetic Algorithms*, pages 385–390, 1989.

[OS94a] D. W. Opitz and J. W. Shavlik. Genetically Refining Topologies of Knowledge-Based Neural Networks. In *International Symposium on Integrating Knowledge and Neural Heuristics*, pages 57–66, Pensacola, FL, May 1994.

[OS94b] D. W. Opitz and J. W. Shavlik. Using Genetic Search to Refine Knowledge-Based Neural Networks. In *Machine Learning: Proceedings of the Eleventh International Conference*, New Brunswick, NJ, July 1994. Morgan Kaufmann.

[Par90] Jan Paredis. The Evolution of Behavior: Some Experiments. In *Simulation of Adaptive Behavior*. 1990.

[PC93] W.J.M. Philipsen and L.J.M. Cluitmans. Using a genetic algorithm to tune Potts neural networks. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 650–657. Springer-Verlag, 1993.

[PCN90] D. Parisi, F. Cecconi, and S. Nolfi. Econets: Neural Networks That Learn in an Environment. *Network*, 1:149–168, 1990.

[PF90] Vincent W. Porto and David B. Fogel. Neural Network Techniques for Navigation of AUVs. In *Proceedings of the IEEE Symposium on Autonomous Underwater Vehicle Technology*, pages 137–141, Washington, DC, 5-6 Jun 1990.

[PKP93] V. Petridis, S. Kazarlis, and A. Papaikonomou. A Genetic Algorithm for Training Recurrent Neural Networks. *Proceedings of IJCNN '93, Nagoya Japan*, pages 2706–2709, 1993.

[PKPF92] V. Petridis, S. Kazarlis, A. Papaikonomou, and A. Filelis. A Hybrid Genetic Algorithm for Training Neural Networks. *proceedings of ICANN '92, Brighton England*, pages 953–956, 1992.

[PKS93] H.B. Penfold, U. Kohlmorgen, and H. Schmeck. Deriving Application-Specific Neural Nets Using a Massively Parallel Genetic Algorithm. Technical Report Parallel GA 004, The University of Newcastle, Australia, 1993.

[PNC91] D. Parisi, S. Nolfi, and F. Cecconi. Learning, Behaviour and Evolution. Technical Report PCIA-91-14, C.N.R. Rome, 1991. Also in Proceedings of the first european conference on artificial life ECAL 91, pp.207-216, Varela,F.J. and Bourgine,P. (Eds).

[Pot92] M.A. Potter. A Genetic Cascade-Correlation Learning Algorithm. In L.D. Whitley and J.D. Schaffer, editors, *Proceedings of COGANN-92 International Workshop on Combinations of Genetic Algorithms and Neural Networks*, pages 123–133. IEEE Computer Society Press, 1992.

[Pra92a] Donald L. Prados. New Learning Algorithm for Training Multilayered Neural Networks that Uses Genetic-Algorithm Techniques. *Electronics Letters*, 28(16):1560–1561, July 1992.

[Pra92b] Donald L. Prados. Training Multilayered Neural Networks by Replacing the Least Fit Hidden Neurons. *Proceedings of IEEE SOUTHEASTCON*, 2:634–637, 1992.

[Rad90] Nicholas J. Radcliffe. Genetic Neural Networks on MIMD Computers. Ph.d. diss, Dept. of Theoretical Physics University of Edinburgh, Edinburgh, Scotland, 1990.

[Raw91] Gregory J. E. Rawlins, editor. *Proceedings of the Workshop on Foundations of Genetic Algorithms*, San Mateo, California, 1991. Morgan Kaufmann.

[Rom93] Steve G. Romaniuk. Evolutionary Growth Perceptrons. In *Proceedings of the Fifth International Conference on Genetic Algorithms*, 1993.

[RS92a] C. Reeves and N. Steele. Problem-Solving by Simulated Genetic Processes: A Review and Application to Neural Networks. In M.H. Hamza, editor, *Proceedings of the Tenth IASTED International Conference. Applied Informatics*, pages 269–272, Zurich, Switzerland, 1992. Acta Press.

[RS92b] W. Rehm and V. Sterzing. An Optimization Method for Multilayer Perceptron Based on Evolution-Theoretic Principles. *Informationstechnik - IT*, 34(5):307–312, Oct 1992.

[RSR93] P. Robbins, A. Soper, and K. Rennolls. Use of Genetic Algorithms for Optimal Topology Determination in Back Propagation Neural Networks. In *Proceedings of the International Conference on Artificial Neural Networks and Genetic Algorithms*, pages 726–730, 1993.

[Rud90] Michael Rudnick. A Bibliography: The Intersection of Genetic Search and Artificial Neural Networks. Cs/e 90-001, Department of Computer Science and Engineering, Oregon Graduate Institute, 1990.

[Rud92] Michael Rudnick. Genetic Algorithms and Fitness Variance with an Application to the Automatic Design of Artificial Neural Networks. Unpublished ph.d. diss, Oregon Graduate Institute of Science and Technology, Portland, OR, 1992.

[Rud93] Michael Rudnick. Evolutionary Network Design and the Contiguity Problem. In *Proceedings of the World Congress on Neural Networks 93*, pages IV135 – IV138. WCNN93, 1993.

[SC94] R. E. Smith and H. B. Cribbs. Is a Learning Classifier System a Type of Neural Network? *Evolutionary Computation*, 1994.

[Sch89] J. David Schaffer, editor. *Proceedings of the Third International Conference on Genetic Algorithms*, San Mateo, California, June 4-7 1989. George Mason University, Morgan Kaufmann.

[SF90] A.V. Sebald and D.B. Fogel. Design of SLAYR Neural Networks Using Evolutionary Programming. In R. R. Chen, editor, *Proceedings of the Twenty-Fourth Asilomar Conference on Signals, Systems and Computers*, volume 2, pages 1020–1024. The Computer Society of IEEE/Maple Press, 1990.

[SF91] A.V. Sebald and D.B. Fogel. Using Evolutionary Neural Networks for Arterial Waveform Discriminiation. In *Proceedings of the International Joint Conference on Neural Networks*, volume II, pages A–955, 1991.

[SFT93a] T. Shibata, T. Fukada, and K. Tanie. Fuzzy Critic for Robotic Motion Planning by Genetic Algorithm in Hierarchical Intelligent Control. In *IJCNN'93-NAGOYA Proceedings of the 1993 International Joint Conference on Neural Networks, Nagoya (Japan)*, pages 770–773. IEEE, 1993.

[SFT93b] T. Shibata, T. Fukada, and K. Tanie. Nonlinear Backlash Compensation Using Recurrent Neural Network - Unsupervised Learning by Genetic Algorithm. In *IJCNN'93-NAGOYA Proceedings of the 1993 International Joint Conference on Neural Networks, Nagoya (Japan)*, pages 742–745. IEEE, 1993.

[SFT93c] T. Shibata, T. Fukada, and K. Tanie. Synthesis of Fuzzy Artificial Intelligence, Neural Networks, and Genetic Algorithms for Heirarchical Intelligent Control. In *IJCNN'93-NAGOYA Proceedings of the 1993 International Joint Conference on Neural Networks, Nagoya (Japan)*, pages 2869–2872. IEEE, 1993.

[SJ90] W.M. Spears and K.A. De Jong. Using Neural Networks and Genetic Algorithms as Heuristics for NP-Complete Problems. In *Proceedings of the International Joint Conference on Neural Networks*, pages 118 – 121, 1990.

[SJW93] W. Schiffmann, M. Joost, and R. Werner. Application of Genetic Algorithms to the Construction of Topologies for Multilayer Perceptrons. In *Proceedings of the International Conference on Artificial Neural Networks and Genetic Algorithms*, pages 675–682, 1993.

[SK91a] Deborah A. Stacey and Stefan Kremer. The Guelph Darwin Project: The Evolution of Neural Networks by Genetic Algorithms. In *Proceedings of the International Joint Conference on Neural Networks*, volume II, pages A–957, 1991.

[SK91b] Keiji Suzuki and Yukinori Kakazu. An Approach to the Analysis of the Basins of the Associative Memory Model Using Genetic Algorithms. In *Proceedings of the Fourth International Conference on Genetic Algorithms*, pages 539–546, 1991.

[SM90] W. Schiffmann and K. Mecklenburg. Genetic Generation of Backpropagation Trained Neural Networks. In R. Eckmiller, G. Hartmann, and G. Hauske, editors, *Parallel Processing in Neural Systems and Computers*, pages 205–208. Elsevier Science Publishers, 1990.

[SM91] Hans-Paul Schwefel and Reinhart Männer, editors. *Proceedings of the First Conference on Parallel Problem Solving from Nature*, volume 496 of *Lecture Notes in Computer Science*, Dortmund, Germany, October 1-3 1991. Springer-Verlag.

[SM92] R. Shonkwiler and Kenyon R. Miller. Genetic Algorithm/Neural Network Synergy For Nonlinear Constrained Optimization Problems. In *Proceedings of the Conference on Combinations of Genetic Algorithms and Neural Networks*, pages 248–257, 1992.

[Smi92] F.J. Smieja. Evolution of Intelligent Systems in a Changing Environment. Gmd-623, Gesellschaft fuer Mathematik und Datenverarbeitung m.b.H., Bonn, Germany, 1992.

[Smi93] Robert E. Smith. Genetic Learning in Rule-Based and Neural Systems. *Proceedings of the Third International Workshop on Neural Networks and Fuzzy Logic*, 1:183, Jan 1993.

[SPM92] C.N. Schizas, C.S. Pattichis, and L.T. Middleton. Neural Networks, Genetic Algorithms and K-Means Algorithm: In Search of Data Classification. In *Proceedings of the Conference on Combinations of Genetic Algorithms and Neural Networks*, pages 201–222, 1992.

[SRM91] David H. Sharp, John Reinitz, and Eric Mjolsness. Genetic Algorithms for Genetic Neural Nets. Research report yaleu/dcs/tr-845, Department of Computer Science, Yale University, Jan 1991.

[SSF92] A.V. Sebald, J. Schlenzig, and D.B. Fogel. Minimax Design of CMAC Encoded Neural Network Controllers Using Evolutionary Programming. *Asilomar Conference on Circuits, Systems & Computers*, 1:551–555, 1992.

[ST92] P. Spiessens and J. Torreele. Massively Parallel Evolution of Recurrent Networks: An Approach to Temporal Processing. In F.J. Varela and P. Bourgine, editors, *Toward a Practice of Autonomous Systems. Proceedings of the First European Conference on Artificial Life*, pages 70–77, Cambridge, MA, USA, 1992. MIT Press.

[SV92] A.V. Scherf and L.D. Voelz. Training Neural Networks with Genetic Algorithms for Target Detection. *Proceedings of the SPIE - The International Society for Optical Engineering*, 1710, pt.1:II–734–II–41, 1992.

[SWBJ90] D.G. Stork, S. Walker, M. Burns, and B. Jackson. Preadaptation in Neural Circuits. In *Proceedings of the International Joint Conference on Neural Networks*, pages I–202 – I–205, 1990.

[SWE92] J. David Schaffer, Darrell Whitley, and Larry J. Eshelman. Combinations of Genetic Algorithms and Neural Networks: A Survey of the State of the Art. In *Proceedings of the Conference on Combinations of Genetic Algorithms and Neural Networks*, pages 1–37, 1992.

[Tac93] Walter Alden Tackett. Genetic Generation of Dendritic Trees for Image Classification. In *Proceedings of the World Congress on Neural Networks*, pages IV646 – IV649, 1993.

[Tak93] Hideyuki Takagi. Neural Network and Genetic Algorithm Techniques for Fuzzy Systems. In *Proceedings of the World Congress on Neural Networks*, pages II631 – II634, 1993.

[TL93] Gabor J. Toth and Andras Lorincz. Genetic Algorithm With Migration on Topology Conserving Maps. In *Proceedings of the World Congress on Neural Networks*, pages III168 – III171. WCNN93, 1993.

[TM] Peter M. Todd and Geoffery F. Miller. Exploring Adaptive Agency II: Simulating the Evolution of Associative Learning. In S. Wilson and J.-A. Meyer, editors, *Proceedings of the International Conference on Simulation of Adaptive Behavior: From Animals to Animats*, pages 306–315. MIT Press.

[Tod88] P. Todd. Evolutionary Methods for Connectionist Architectures. unpublished internal report, Stanford, 1988.

[Tor91] J. Torreele. Temporal Processing With Recurrent Networks: An Evolutionary Approach. In R.K. Belew and L.B. Booker, editors, *Proceedings of the Fourth International Conference on Genetic Algorithms*, pages 555–561. Morgan Kaufmann, 1991.

[TR92] Louis A. Tamburino and Mateen M. Rizki. Performance-Driven Autonomous Design of Pattern-Recognition Systems. *Applied Artificial Intelligence*, 6(1):59–77, 1992.

[TSVN93] D. Thierens, J. Suykens, J. Vandewalle, and B. De Noor. Genetic Weight Optimization of a Feedforward Neural Network Controller. In R.F. Albrecht, C.R. Reeves, and N.C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms Proceedings of the International Conference at Innsbruck, Austria*, pages 658–663, Wien and New York, 1993. Springer.

[UP93] T. Uthmann and D. Polani. Training Kohonen Feature Maps in Different Topologies: An analysis using Genetic Algorithms. In *Proceedings of the International Conference on Genetic Algorithms*, 1993.

[UV63] L. Uhr and C. Vossler. A Pattern Recognition Program that Generates, Evaluates and Adjusts its Own Operators. In E. Feigenbaum and J. Feldman, editors, *Computers and Thought*. McGraw-Hill, New York, 1963.

[Vaa93] Jari Vaario. *An Emergent Modeling Method for Artificial Neural Networks*. PhD thesis, The University of Tokyo, 1993.

[Vaa94a] Jari Vaario. Artificial Life as Constructivist AI. *Journal of SICE (Japanese Society of Instrument and Control Engineers)*, 33(1):65–71, 1994.

[Vaa94b] Jari Vaario. From Evolutionary Computation to Computational Evolution. *Informatica*, 1994. (to appear).

[Vaa94c] Jari Vaario. Modeling Adaptative Self-Organization. In *Proceedings of Artificial Life IV*, July 6-8 1994.

[VBSK93] H-M. Voigt, J. Born, and I. Santibanez-Koref. Evolutionary Structuring of Artificial Neural Networks. Technical Report TR-02-93, Bionics and Evolution Techniques Laboratory, Technical University Berlin, 1993.

[Vem92] V. Vemuri. Neural Networks Can be Used for Open-Loop, Dynamic Control. *International Journal of Neural Networks*, 2:71–84, 1992.

[VHO94] Jari Vaario, Koichi Hori, and Setsuo Ohsuga. Toward Evolutionary Design of Autonomous Systems. *The International Journal in Computer Simulation*, 1994. (to appear).

[VO91] Jari Vaario and Setsuo Ohsuga. Adaptive Neural Architectures through Growth Control. In *Intelligent Engineering Systems through Artificial Neural Networks*, pages 11–16. 1991.

[VO92] Jari Vaario and Setsuo Ohsuga. An Emergent Construction of Adaptive Neural Architectures. *Heuristics - The Journal of Knowledge Engineering*, 5(2), 1992.

[VO94] Jari Vaario and Setsuo Ohsuga. On Growing Intelligence. In *Neural Networks and a New AI*. 1994.

[VOH91] Jari Vaario, Setsuo Ohsuga, and Koichi Hori. Connectionist Modeling Using Lindenmayer Systems. In *Information Modeling and Knowledge Bases: Foundations, Theory, and Applications*, pages 496–510. 1991.

[VS91] F.J. Vico and F. Sandoval. Use of Genetic Algorithms in Neural Networks Definition. In A. Prieto, editor, *Artificial Neural Networks, IWANN91, Granada*, pages 196–203. Lecture notes in Computer Science 540, Springer Verlag, 1991.

[VS92] F.J. Vico and F. Sandoval. Neural Networks Definition Algorithm. *Microprocessing and Microprogramming*, 34(1-5):251–254, 1992.

[WB90] D. Whitley and C. Bogart. The Evolution of Connectivity: Pruning Neural Networks Using Genetic Algorithms. In *Proceedings of the International Joint Conference on Neural Networks*, pages 134–137. IEEE Press, 1990.

[WB93] B.V. Williams and D.G. Bounds. Learning and Evolution in Populations of Backprop Networks. In *Proceedings of ECAL93 – European Conference on Artificial Life*, 1993.

[WBBH94] B. V. Williams, R. T. J. Bostock, D. G. Bounds, and A. J. Harget. Improving Classification Performance in the Bumptree Network by Optimising Topology with a Genetic Algorithm. In *IEEE Evolutionary Computation 1994*, 1994.

[WC94] B.A. Whitehead and T.D. Choate. Evolving Space-Filling Curves to Distribute Radial Basis Functions Over an Input Space. *IEEE Transactions on Neural Networks*, 5:15–23, 1994.

[WD90] G.M. Werner and M.G. Dyer. Evolution of Communication in Artificial Organisms. Technical Report UCLA-AI-90-06, AI Lab, UCSD, 1990.

[WD91] G.M. Werner and M.G. Dyer. Evolution of Communication in Artificial Organisms. In *Artificial Life II: Proceedings of the Workshop on Artificial Life Held in 1990*, pages 659–687, 1991.

[WDD91a] D. Whitley, S. Dominic, and R. Das. Genetic Reinforcement Learning with Multilayer Neural Networks. In R. K. Belew and L. B. Booker, editors, *Proceedings of the Fourth International Conference on Genetic Algorithms*, pages 562–569. Morgan Kaufmann, San Mateo, CA, 1991.

[WDD91b] Darrell Whitley, Stephen Dominic, and Rajarshi Das. Genetic Reinforcement Learning with Multilayer Neural Networks. In *Proceedings of the International Conference on Genetic Algorithms*, pages 562–5769, 1991.

[WDDA92] Darrell Whitley, S. Dominic, R. Das, and C. Anderson. Genetic Reinforcement Learning for Neurocontrol Problems. Machine Learning, 1992.

[Wei90] G. Weiss. Combining Neural and Evolutionary Learning: Aspects and Approaches. Tum fki-132-90, Technical University of Munich, May 1990.

[WH89] D. Whitley and T. Hanson. Optimizing Neural Networks Using Faster, More Accurate Genetic Search. In J.D. Schaffer, editor, *Proceedings of the Third International Conference on Genetic Algorithms*, pages 391–396. Morgan Kaufmann, 1989.

[Whi88a] Darrell Whitley. Applying Genetic Algorithms to Neural Network Learning. Technical Report CS-88-128, Department of Computer Science, Colorado State University, 1988. Also appeared in: Proceedings of the 7th Conference for the Study of Artificial Intelligence and Simulated Behavior, Sussex, England 1989. Pitman Publishers.

[Whi88b] Darrell Whitley. Applying Genetic Algorithms to Neural Network Problems: A Preliminary Report. In *Proceedings of the International Neural Network Society Conference*. PROC INNS88, 1988.

[Whi89a] Darrell Whitley. Genetic Algorithm Applications: Neural Nets, Traveling Salesmen and Schedules. In *Proceedings of the 1989 Rocky Mountain Conference on Artificial Intelligence*, Denver, CO, 1989.

[Whi89b] Darrell Whitley. *Optimizing Neural Networks Using Genetic Algorithms*. Markt and Technik, Munich, Germany, 1989.

[Whi93] Darrell L. Whitley, editor. *Proceedings of the Workshop on Foundations of Genetic Algorithms*, San Mateo, California, 1993. Morgan Kaufmann. The second workshop on Foundations of Genetic Algorithms (FOGA) was held July 26-29, 1992 in Vail, Colorado.

[Wie90] Alexis P. Wieland. Evolving Controls for Unstable Systems. In D.S. Touretzky, J.L. Elman, T.J. Sejnowski, and G.E. Hinton, editors, *Proceedings of the 1990 Connectionist Models Summer School*, pages 91–102. Morgan Kaufman, 1990.

[Wie91] Alexis P. Wieland. Evolving Neural Network Controllers for Unstable Systems. *IJCNN-91*, II:667–673, 1991.

[Wil90] Stewart W. Wilson. Perceptron Redux: Emergence of Structure. In Stephanie Forrest, editor, *Emergent Computation*, pages 249–256. North Holland, Amsterdam, 1990.

[Wil93] Peter Wilke. Simulation of Neural Network and Genetic Algorithms in a Distributed Computing Environment Using NeuroGraph. In *Proceedings of the World Congress on Neural Networks*, pages I269 – I272, 1993.

[WO] C. L. Wilson and O.M. Omidvar. Optimization of Neural Network Topology and Information Content Using Boltzmann Methods. NIST ir4766, at the NIST archive, ???? available via ftp from (the NIST archive).

[WPM93] Kevin W. Whitaker, Ravi K. Prasanth, and Robert E. Markin. Specifying Exhaust Nozzle Contours With a Neural Network. *AIAA Journal*, 31(2):273–277, Feb 1993.

[WS92] L. D. Whitley and J. D. Schaffer, editors. *International Workshop on Combinations of Genetic Algorithms and Neural Networks: COGANN-92*, Los Alamiitos, California, 1992. IEEE Computer Society Press.

[WSB90] D. Whitley, T. Starkweather, and C. Bogart. Genetic Algorithms and Neural Networks: Optimizing Connections and Connectivity. *Parallel Computing*, 14-3:347–361, 1990.

[Yae94] Larry Yaeger. Computational Genetics, Physiology, Metabolism, Neural Systems, Learning, Vision and Behavior or PolyWorld: Life in a New Context. In C. G. Langton, editor, *Artificial Life III, Proceedings Volume XVII*, pages 263–298. Santa Fe Institute Studies in the Sciences of Complexity, Addison-Wesley, 1994.

[Yao92] Xin Yao. A Review of Evolutionary Artificial Neural Networks. Technical report, Commonwealth Scientific and Industrial Research Organization, Division of Building, Construction and Engineering, PO Box 56, Highett, Victoria 3190, Australia, 1992.

[Yao93] Xin Yao. A Review of Evolutionary Artificial Neural Networks. *International Journal of Intelligent Systems*, 8(4):539–67, April 1993.

[YY93] T. Yamada and T. Yabuta. Remarks on Neural Network Controller Which Uses Genetic Algorithm. In *IJCNN'93-NAGOYA Proceedings of the 1993 International Joint Conference on Neural Networks, Nagoya (Japan)*, pages 2783–2786. IEEE, 1993.

[ZM93] Byoung-Tak Zhang and H. Műhlenbein. Genetic Programming of Minimal Neural Nets Using Occam's Razor. In *Proceedings of the International Conference on Genetic Algorithms*, 1993.

[ZV91] Byoung-Tak Zhang and Gerd Veenker. Neural Networks that Teach Themselves Through Genetic Discovery of Novel Examples. In *Proceedings of the International Joint Conference on Neural Networks*, pages 690–695, 1991.