N88-17218

NEURAL NETWORK BASED ARCHITECTURES FOR AEROSPACE APPLICATIONS

by

Richard Ricart, 2Lt
System Avionics Division
Avionics Laboratory
Air Force Systems Command
United States Air Force
Wright-Patterson Air Force Base, Ohio

ABSTRACT

The recent fervor and reemergence of research in neural networks has its reasons. The most important are the ability of these systems to store vast numbers of complex patterns, the ability to recall these patterns in O(1) time (i.e., speed of pattern retrieval is independent of number of stored patterns), and the ability to recall these stored patterns using fuzzy or incomplete cues.

In this paper, a brief history of the field will be reviewed and some simple concepts will be described. In addition, some neural network based avionics research and development programs will be reviewed. The concluding remarks will stress the need for the United States Air Force (USAF) and the National Aeronautics and Space Administration (NASA) to assume a leadership role in supporting this technology.

INTRODUCTION

The System Evaluation Branch of the Avionics Laboratory at Wright-Patterson Air Force Base is currently working under a charter to transfer learning research to exploratory development of intelligent electronic combat systems. Neural networks have been identified by this group as having great potential for solving a variety of difficult problems encountered in military avionics.

The purpose of this paper is to show the need for new approaches in developing intelligent systems for the USAF. It can be argued that this need also applies to NASA and the aerospace industry in general. The argument for why neural networks have the potential for satisfying this need will be given by introducing some important properties of neural networks. A brief historical perspective of the field and the current trends in the technology will also be provided. In addition, a brief description of the research and development programs being conducted and planned by the Software Development Group will be given.

NEED FOR NEW APPROACHES IN THE AIR FORCE TO DEVELOPING INTELLIGENT SYSTEMS

The environments in which our military aircraft and weapons systems must operate in have become increasingly complex and hostile with the advancement of technology. Survival will depend on developing autonomous, flexible avionics systems that can adapt and learn from a highly dynamic and hostile environment. However, this is a tremendous challenge due to the complexity of these systems and their environments. The usual problem domains encountered in electronic combat systems, for example, can be characterized as follows: A usually small number of resources must be managed and allocated to satisfy multiple constraints and optimization criteria. These systems are capable of multiple responses under multiple threat and/or target environments. Changes to the environment usually occur very rapidly and sometimes unexpectedly. These systems must process a tremendous amount of information under conditions of novelty, deception, incomplete data, and noise. A further crucial requirement is that these processes must be accomplishable in real-time.

Artificial Intelligence (AI) is one approach to developing "intelligent" systems, but current AI technology has many limitations. The problem domains under which most AI technology has been developed are very different than the problem domains of many military and aerospace applications. The problem domains most expert systems have dealt with have been quite narrow, ideal, and free of noise. Most importantly, processing time has not been a critical factor. AI and other traditional problem solving techniques have had difficulty dealing with many areas such as machine vision, automatic target recognition, situation assessment, and resource planning and control, to name a few. The real-time constraints have been one of the factors contributing to the difficulty in developing AI based solutions to the problems mentioned above.

O'Reilly & Cromarty (1985) have formally defined real-time system performance as the requirement that a system's response to environmental stimuli occur in *provably* finite time (i.e., O(1) time response). The authors show that current AI and traditional problem solving approaches cannot prove this time response and go on to say:

> "...our analysis indicates that there is no reason to expect conventional system design approaches from either school to yield effective, provable real-time performance."

They further propose that parallelism is one way of achieving this performance.
This analysis is consistent with the general acceptance

in the AI community for the need of parallelism in their problem solving approaches.

There has been considerable work in recent years in parallel processing, but developments in hardware have far outstripped the programmers ability to effectively use these systems. We are having problems developing parallel algorithms. This problem is exemplified by the title of a recent paper, *Programming for parallelism: The state of the art of parallel programming and what a sorry state that art is in* (Karp, 1987).

Because of the limitations and slow progress in current AI research and development, especially as it relates to real-world military and aerospace operations, there has been a growing need to re-evaluate research strategies. One alternative approach which has a strong potential for satisfying the Air Force's need for intelligent systems, is *neural networks*.

NEURAL NETWORK SYSTEMS: THEIR PROPERITIES

Neural networks have properties which seem to offer solutions to many of the difficult problems encountered in machine learning, vision, speech, pattern recognition, and real-time resource planning and control. These properties are all interrelated, making it difficult identify the most important one. The remainder of this section will concentrate on explaining these properties.

Most neural networks are modeled after or resemble some of the structure and function of biological* brains and nerve cells (neurons), thus their name. These systems are composed of interconnected processing elements (PEs) or "neurons" which process information in parallel. The PEs have multiple inputs (from the output of other neurons or from external stimuli) and a single output. This output may in turn branch out to yet other PEs or the outside world. Neural networks are inherently parallel processing systems.

An important class of neural networks have the ability to learn and adapt in response to environmental changes. In these neural networks, the PE's have self adjusting weights associated with their input channels (i.e., the conductance of the interconnections change with experience). This self adjusting of network parameters is the basis of learning in neural networks and is one of the most important characteristics of these systems.

One very useful way of interpreting the dynamics of a neural network is as an energy field undergoing changes over time. One can think of this energy field as a flat sheet (it is actually a multidimensional surface). As the network interacts with its environment, wells or basins are created or formed on this flat sheet over time. If the job of the network is to identify or categorize signals of some kind, these wells represent the learned categories. The input stimuli can be thought of as marbles. As new marbles (input stimuli) fall onto this contoured sheet (energy field), the marbles will roll into the closest basin. Marbles that fall into a particular well are similar to the marbles that created the well to begin with. This brings us to the next set of related properties of neural networks. These systems are capable of associating arbitrary input states with the nearest energy basin (identification, category, or response). In addition, these systems decide what the appropriate features of the input states are in order to make the classifications or responses. Therefore, neural networks can act as associative memories, nearest neighbor pattern classifiers, and feature detectors (Kohonen, 1984; Kosko, 1986 and 1987a).

A very important result in neural network research, the Cohen/Grossberg Theorem (Cohen & Grossberg 1983), was popularized in a similar finding by Hopfield (1982 and 1984). This theorem states that the energy of a class of neural networks, called Crossbar Associative Networks (CANs), converges to a finite set of equilibrium points. The energy of the system is defined as a global Liapunov function and the equilibrium points are the local minima of that function. Not only is convergence guaranteed, but the time required to converge to those equilibrium points does not depend on the number of those points. In other words, CANs respond in $O(1)$ time. This is a characteristic of every neural network.

Just as in conventional AI programs, knowledge representation is of utmost importance in neural networks. But knowledge is distributed throughout* a massively interconnected processor architecture. For example, a certain neural network might have the concept of an airplane represented in its network. That concept will be distributed among many PEs and each PE will contain small pieces of information about other concepts; maybe tank, helicopter, jeep, etc. Due to the networks ability to utilize distributed knowledge representations which are supported by massive numbers of parallel elements, these networks are fault tolerant. Neural networks have been shown to exhibit graceful degradation of performance as more PEs become inoperative (Anderson, 1983). One can understand why this occurs from the example of the airplane above. If one or two elements which contain information about that airplane are damaged, the remainder of the network may contain enough of the concept "airplane" to use that information effectively in some type of process. If any piece of hardware or software in conventional computers becomes corrupted, there will be system failure.

---

*Although there is still considerable disagreement among psychologists on the principles of information processing of the brain, and many neurological functions and cellular mechanisms have not been resolved, mathematical models of certain structures and functions of the brain have been developed with characteristics similar to known neurological functions.

*Many networks have been developed in which knowledge was not distributed. Each PE represented one and only one concept. In these experiments other properties and capabilities of neural networks were being examined which did not require distributed representations.

One final, very important characteristic which is sure to have a considerable impact on the aerospace industry, is that these systems process information without the use of computer programs. What is required is the specification and development of an architecture of interconnected PEs for a given problem. Each PE of the neural network is governed by a system of mathematical equations which can be implemented directly in electronic circuitry. After an architecture is defined, the neural network is then put through a training or learning stage. It is in this stage that the system learns the appropriate I/O mappings with either the help of a "teacher" or "critic", or on its own* if enough a priori information is built into the system. Still other systems can learn continuously as they interact with their environments.

Before leaving this section, a brief, high level description of the mathematical equations governing a neural network will be given. The typical PE is governed by usually two or three differential equations (or difference equations when dealing in discrete time). One equation determines the activity or state of the PE, another determines the change in conductances (or the final values of the conductances after the network settles to a stable state) of the PE's input channels, and the third equation determines the output of the PE. When the PEs are governed by two equations, the activity of the PE is usually incorporated into the output equation. The activity equations are usually some function of the sum of the weighted inputs. The output equations are usually a nonlinear function of the activity (either sigmoid or linear threshold). And the change in input conductances are usually some function of the inputs, output, and the conductances themselves.

These dynamical equations come in a variety of forms which have either evolved or have been added over the years to give us a large and rich repertoire today. This variety reflects the diverse and interdisciplinary background of the researchers in the field: neuroscience, psychology, physics, mathematics, engineering, and computer science.

A number of important attributes of neural networks have been discussed. It must be emphasized, however, that the engineering process of developing architectures, especially for real world problems, is still in its infancy. Convergence theorems for many classes of important neural networks have not been found. Fortunately, we do have enough empirical data to suggest that convergence proofs to some of these systems may be found. Other problems include strict limits on the amount of data storage imposed on a neural network of given size and the ability of associative memories to create spurious energy minima (Kosko 1987a). The important point to stress is that neural networks offer a tremendous *potential* for solving many difficult problems which solutions have not been previously, or acceptably found. But before this potential is realized, much work needs to be done.

---

*More detailed discussions on the different classes of learning and how these are accomplished in neural networks are discussed in Duda & Hart (1973), Barto & Sutton (1981), and Barto (1985).

HISTORY AND CURRENT TRENDS

In this section, a brief history and the current trends in neural network research will be introduced in order to give a general feel for the field. For a comprehensive review see Levine (1983). Barto (1984) also presents a more in depth review than the one found here. Probably the best introduction to neural networks is provided by Rumelhart, et al (1986). This work also includes research more appealing to those with AI and cognitive science backgrounds.

The early concepts of processing information by a network of simple linear threshold elements were introduced by McCulloch and Pitts (1943). They developed very simple linear threshold processing elements with boolean output which were interconnected via positive and negative input lines. Their results generated much excitement for they showed any logical function could be performed by some configuration of such networks.

The next major milestone was achieved by Hebb (1949) when he postulated a mechanism for long term memory. This mechanism required a structural change to the neuron:

> "When the axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased (Hebb, 1949, p. 64)"

This hypothesis was later interpreted mathematically as

$$\frac{d}{dt} w_i = x_i y$$

where w_i is the weight associated with the ith input to the neuron, x_i is the ith input signal from another neuron, and y is the output of the neuron in question. This rule has had a tremendous impact on neural network research for it has been used in one form or another in virtually every learning neural network conceived.

It wasn't until the late 50s and early 60s that neural networks were developed along the lines in which we are familiar with today. McCulloch and Pitts' ideas of interconnected linear threshold elements and Hebb's ideas of long term memory were integrated into very useful devices. Two such systems deserve special attention: The Perceptron, developed by Rosenblatt (1962) and the Adaline (for adaptive logic element), developed by Widrow (1962). Both of these systems were similar in that they were based on a single adaptive layer of neurons and on an error correcting mechanism. The difference between the desired response and the actual response was fed back to the adaptive layer through a series of training trials until the network converged to a solution in provable finite time.

Unfortunately for Rosenblatt and for neural network research for the next 20 years or so, Rosenblatt made claims which seemed unfounded to several of his contemporaries. This led to Minsky and Papert's (1969) critical response to the Perceptron (see Rumelhart, et al, 1986, pp. 151-159). Minsky and Papert showed a number of limitations of single layered adaptive networks and also raised the issue of the credit assignment problem in multilayered networks of error correcting elements. The credit assignment problem arises as a result of the inability of cells within the interior layers of the network to know what fraction of the total error they are responsible for. These problems have been solved in a variety of ways since then (Parker, 1982 and 1985, and Rumelhart, et al, 1985), but in those days they raised alarming questions.

Minsky and Papert's book was devastating to Rosenblatt and neural network research. The book was a sign to many that research should be directed towards symbolic processing and heuristics. This approach is what we know as AI today. The push for this approach was also being heavily influenced by the growing field of cognitive psychology (for a historical view from this perspective see Gardner, 1985). At this same time, behaviorist psychology was in decline. This also helped sway research funds away from neural networks since the issues involved in neural networks were highly reminiscent of the issues the behaviorists were grappling with: stimulus/response chains, reinforcement, and behavior based on microstructural concepts.

Widrow, on the other hand, was extremely successful applying his Adaline and Madaline (for many Adalines) to signal processing. His adaptive signal processing techniques have been applied to system modeling (i.e., imitating system behavior), inverse system modeling, adaptive control systems, adaptive interference canceling, and to adaptive antenna arrays (Widrow, 1985). It is also interesting to point out Widrow's achievements in the 60s. His Knobby Adaline (a hardware implementation of his adjustable threshold element, Widrow 1962) was able to recognize patterns regardless of noise (10%), rotation (90 degrees), left and right translation, and size (25%). The Avionics Laboratory, at Wright-Patterson Air Force Base owns a film* of a pole balancing experiment performed by Widrow. A small cart with a pole attached to the top of the cart by a pivot was placed on a short track. The Madaline was able to keep the pole balanced by controlling the cart's movement after a series of training trials. In that same film, Widrow's students are shown training a Madaline to translate spoken words in three languages to type written English. One may wonder whether the neural network "nuclear winter" that ensued would have taken place if these results would have been marketed as vigorously as the limitations to the technology at the time.

Although neural network modeling fell from grace after Minsky and Papert's book, very important work continued throughout the 70s. Fukushima (1975) and von der Marlsburg (1973) developed systems based on the visual structures of biological brains. Kohonen (1972) and Wilshaw, et al (1970 and 1971) were early pioneers in the area of associative memories. Amari, et al (1974 and 1977) made an important contribution through his research in associative memories and their relation to thermodynamics. Klopf (1972 and 1979) introduces the concept of the neuron as a goal oriented or goal seeking agent (heterostat). Rescorla and Wagner (1972) developed a model which exhibited a variety animal learning phenomena.

*The USAF supported Widrow's research as well as other neural network research in those early days.

The most prolific contributor to this field has been Stephen Grossberg, of the Center for Adaptive Studies, at Boston University. Grossberg has addressed all the main issues in neural networks from 1967 (Grossberg, 1967) to date in approximately 130 papers and 4 books. He has approached his research with rigorous mathematics and has proved some of the most important theorems in the field. He has investigated and written about memory, animal learning behavior, cognition, speech, language, vision, and motor control. He's collected his most important work in three volumes (Grossberg, 1982, 1987a, and 1987b).

John Hopfield of Caltech and Bell Labs is, perhaps, the one most responsible for reigniting the field. In two articles (Hopfield, 1982 and 1984), Hopfield, expanding on previous work on crossbar associative networks (CANs), made connections between CANs and Ising spin glass models of ferromagnetism. Hopfield's papers made a strong impact on the physics and optics community in a series of conference presentation. Hopfield and Tank (1985) further publicized the information processing capabilities of neural networks by developing a CAN system which had the ability to find near optimum solutions to a traveling salesman problem. In other words, they developed an O(1) time approximate solution to a NP-hard problem using neural networks (see Hecht-Nielsen, 1986 for this discussion). Interest in the field has mushroomed in academia, the Department of Defense, and throughout the aerospace industry since Hopfield's 1982 paper.

Today, theoretical work continues at a fast pace from many of the original pioneers mentioned above and from scores of others entering this exciting field. Over 200 papers were presented in 16 sessions at the Institute of Electrical and Electronics Engineers (IEEE) sponsored First Annual International Conference on Neural Networks in San Diego, California, between the 21st and 24th of June, 1987. Nearly 2,000 people were attracted to this event. The 80s have also brought much needed work in the hardware implementation of neural networks. In the past, almost all work was simulated on general purpose computers. Experiments could run for days in those early years. Special purpose processors are coming to market today which can significantly increase processing speed. For many applications, these are sufficient for real-time processing. For more difficult problems such as vision or target recognition, much larger networks will be required. If these networks are to be flown in spacecraft and aircraft, they'll have to be implemented in silicon, optics, or a combination of both. Fortunately, work is well under way addressing this need. The following is only a small sampling of optical and electronic neural network research: Cruz-Young & Tam, 1985; Dunning, et al, 1986; Graf & deVegvar, 1987a and 1987b; Fisher, et al, 1986; Psaltis and Abu-Mostafa, 1985; Psaltis and Farhat, 1985; Sivilotti, 1985; and Soffer, 1986.

SYSTEM EVALUATION BRANCH's (AAAF) R&D EFFORTS

Basic research in neural networks has matured to a point suitable for translation into exploratory development. AAAF's efforts are aimed at advancing neural network research in both the signal processing and cognitive processing areas for avionics applications.

The ultimate goal is to merge both areas of research and develop the technology for providing intelligent avionics sensor systems for the USAF. We are specifically addressing the avionics domain from the level of sensors and emitters in electronic combat applications. This research is part of a long term program, *Intelligent Avionics*, which is in general addressing the issue of making avionics adaptive. Both contracted and in-house efforts will be conducted under this program.

Two contracts are currently being managed in the neural network area. The first is the *Adaptive Network Cognitive Processor* (ANCP), a one year effort which was awarded to TRW in San Diego, California. The purpose of this program is to develop a prototype system which builds an inner model of its environment in the form of cognitive maps and uses this model for reasoning, planning, or problem solving. The exact problem domain is a high level situation assessment and response system for pilot aiding. This is a "proof of concept" program. A TRW Mark III neurocomputer is being used for neural network design and simulation and will be delivered as part of the prototype.

The second program, the *Adaptive Network Sensor Processor*, will apply neural network associative memory and pattern recognition technology to a military radar warning system for providing identification, categorization, and classification of previously experienced and novel radar signals in a noisy and corruptive environment. A comparison between this new approach to radar signal identification and conventional means of signal processing will be accomplished before system delivery. There are two contractors working on this program: Booz-Allen & Hamilton, Inc. from Arlington, Virginia and Texas Instruments from Dallas, Texas. A Hecht-Nielsen Neurocomputer Company (HNC) ANZA neurocomputer will also be used by Booz-Allen & Hamilton. Texas Instruments will be using their array processor board, the Odyssey, in conjunction with their Explorer work station for developing and simulating the neural network and environment.

Follow-on efforts for both of these programs are being planned. The *Adaptive Network Avionics Resource Manager* (ANARM) will apply what is learned in ANCP to a specific electronic combat system. The *Adaptive Network Radar Signal Processor* will integrate ANSP with a response module to provide closed loop learning. Hardware implementation issues will also be investigated. These programs are scheduled to start in fiscal year 1988 and fiscal year 1989 respectively.

In-house research is also being conducted under a program entitled *Real-time Adaptive Avionics.* As part of this effort, a neural network design tool was developed and implemented on an LMI (now Giga Mos) Lambda LISP Machine. The *Artificial Neural Design Environment* (ANDE) has been used to investigate the application of Klopf's (1986) Drive-Reinforcement Neuronal Model to a simulated avionics control problem. The ultimate goal of this research is to transfer a neural network architecture to electronic combat groups which can perform real-time, adaptive resource management and control. Support for this research is being pursued from the Air Force Office of Scientific Research (AFOSR).

CONCLUSION

The United States Air Force and the National Aeronautics and Space Administration should assume a leadership role in advancing neural network research and development efforts because of the tremendous potential for providing adaptive, fault-tolerant aerospace systems. We have available to us a viable technological alternative which offers potential solutions to such complex problems as data fusion, machine vision, automatic target recognition, resource planning and control, and adaptive system control. The important characteristics of neural network, which are summarized below, must be exploited and used in innovative ways in order for this potential to be realized. Neural networks are parallel processing systems that can respond in $O(1)$ time. These systems can learn and adapt to their environment and are fault tolerant to damage. And finally, neural networks can process information without the need of computer programs. The foreseen software explosion and crisis could be diminished or alleviated.

Neural network technology will not supplant current computer science and software development where these are more appropriate. Rather, hybrid systems are envisioned with each technology performing what it does best. New developments in neural network technology, however, have the potential to revolutionize and greatly enhance intelligent information processing for our country's defense and space science. It is also clear that the USAF and NASA should steer the research efforts in this area in order that neural network technology develops in a manner suited to aerospace requirements. The System Evaluation Branch of the Avionics Laboratory at Wright-Patterson Air Force Base is committed to develop and exploit this "new" technology for developing intelligent avionics systems.

ACKNOWLEDGEMENTS

Special thanks to Lt Mark Peot for his valuable comments and assistance.

REFERENCES

Amari, S., "A Method of Statistical Neurodynamics", *Kybernetik, Biological Cybernetics, 1974*, Vol. 14, pp. 201-225.

Amari, S., Yoshida, K. and Kanatani, K.,"A Mathematical Foundation for Statistical Neurodynamics", *SIAM J. Appl. Math*, Vol. 33, No. 1, 1974, pp. 95-126.

Anderson, J.A. "Cognitive and Psychological Computation with Neural Models", *Transactions on Systems, Man, and Cybernetics*, Vol. SMC-13, No. 5, Sept/Oct, 1983, pp. 799-815.

Barto, A.G., ed., "Simulation Experiments with Goal-Seeking Adaptive Elements", *Air Force Wright Aeronautical Laboratories/ Avionics Laboratory Technical Report AFWAL-TR-84-1024*, Wright-Patterson AFB, OH., 1984.

Barto, A.G., "Learning by Statistical Cooperation of Self-interested Neuron-like Computing Elements", *Human Neurobiology*, Vol. 4, 1985, pp. 229-256.

Barto, A.G. and Sutton, R.S., "Goal Seeking Components for Adaptive Intelligence: An Initial Assessment", *Air Force Wright Aeronautical Laboratories/ Avionics Laboratory Technical Report AFWAL-TR-81-1070*, Wright-Patterson AFB, OH., 1981.

Cohen, M. and Grossberg, S., "Absolute Stability of Global Pattern Formation and Parallel Storage by Competitive Neural Networks", *IEEE Trans. of Sys., Man, and Cybernetics, SMC-13*, 1983, pp. 815-926.

Cruz-Young, C. and Tam, J.Y., "NEP: An Emulation Assist Processor for Parallel Associative Networks", IBM Palo Alto Scientific Center Report No. 6320-3475, 1985.

Dunning, G.J., Marom, E., Owechko, Y., and Soffer, B.H., "Optical Holographic Associative Memory Using a Phase Conjugate Resonator", *Proc. SPIE*, 1986, p. 625.

Duda, R.O. and Hart, P.E., *"Pattern Classification and Scene Analysis"*, Wiley, New York, 1973.

Fisher, A.D., Jukuda, R.C. and Lee, J.N., "Implementation of Adaptive Associative Optical Computing Elements", *Proc. SPIE*, 1986, p. 625.

Fukushima, K., "Cognitron: A Self-Organizing Multi Layered Neural Network", *Biol Cybernetics*, 20, Nov., 1975, pp.121-136.

Gardner, H., *"The Mind's.New Science"*, Basic Books, Inc., New York, 1983.

Graf, H.P., and deVegvar, P., "A CMOS Associative Memory Chip Based on Neural Networks", *Digest, ISSCC*, Vol. 304, New York, 1987a.

Graf, H.P., and deVegvar, P., "A CMOS Implementation of a Neural Network Model", *Proc., Stanford Conf. Advanced Research in VLSI*, March, MIT Press, 1987b.

Grossberg, S., "Nonlinear Difference-Differential Equations in Prediction and Learning Theory", *Proc., Nat'l Acad. Sci.*, Vol. 58, 1967, pp. 1329-1334.

Grossberg, S., *"Studies of Mind and Brain"*, Boston: Reidel Press, 1982.

Grossberg, S. ed., *"The Adaptive Brain I: Coginition, Learning, Reinforcement, and Rhythm"*, Amsterdam: North-Holland, 1987a.

Grossberg, S. ed., *"The Adaptive Brain II: Vision, Speech, Language and Motor Control"*, Amsterdam: North-Holland, 1987b.

Hebb, D.O., *"The Organization of Behavior"*, Wiley, New York, 1949.

Hecht-Nielsen, R., Technical paper "Artificial Neural Systems Technology", Unpublished technical paper, TRW,Rancho Carmel AI Center, San Diego CA., 1986.

Hopfield, J.J., "Neural Networks and Physical Systems with Emergent Collective Computational Abilities", *Proc., Nat'l Acad. Sci.*, Vol. 79, 1982, pp. 2554-2558.

Hopfield, J.J., "Neurons with Graded Response Have Collective Computational Properties Like Those of Two-State Neurons", *Proc. Nat'l Acad. Sci.*, Vol. 81, May, 1984, pp. 3088-3092.

Hopfield, J.J. and Tank, D.W., "Neural: Computation of Decisions in Optimization Problems", *Biol Cybern.*, Vol. 52, 1985, pp. 141-152.

Karp, A.H., "Programming for Parallelism: The State of the Art of Parallel Programming and What a Sorry State That Art Is In", *Computer*, Vol. 20, No. 5, Computer Society of the IEEE, 1987, pp. 43-57.

Klopf, A.H., "Brain Function and Adaptive Systems: A Heterostatic Theory", *Air Force Cambridge Research Laboratories Research Report AFCRL-72-016 4*, Bedford, Mass, 1972..

Klopf, A.H., "Goal-Seeking Systems from Goal-Seeking Components", *Cogn and Brain Theory Newsl. 3*, No. 2., 1979.

Klopf, A.H., "A Drive-Reinforcement Model of SingleNeuron Function: An Alternative to the Hebbian Neuronal Model", In J.S. Denker (Ed.), *Neural Networks for Computing*, AIP Conference Proceedings 151, New York: American Institute of Physics, 1986, pp. 265-270.

Kohonen, T., "Correlation Associative Memories", *IEEE Transactions on Computers"*, Vol. C-21, 1972, p. 353.

Kohonen, T., *"Self-Organization and Associative Memory"*, Springer-Verlag, New York, 1984.

Kosko, B., "Fuzzy Associative Memories", In A. Kandel Ed., *Fuzzy Expert Systems*, Addison-Wesley, 1986.

Kosko, B., "Bidirectional Associative Memories" *Proc., SPIE: Image Understanding*, Vol. 758, Jan, 1987a.

Kosko, B., "What is an Associative Memory?" In review, 1987b.

Levine, D.S., "Neural Population Modeling and Psychology: A review", *Mathematical Biosciences*, Vol. 66, 1983, pp. 1-86.

McCulloch, W.S. and Pitts, W., "A Logical Calculus of the Ideas Immanent in Nervous Activity", *Bulletin of Mathematical Biophysics*, Vol. 5, 1943, pp. 115-133.

Minsky, M.L., and Papert, S., *"Perceptrons: An Introduction to Computational Geometry"*, Cambridge, MA: MIT Press, 1969.

O'Reilly, C.A. and Cromarty, A.S., "Fast Is Not Real-Time: Designing Effective Real-Time AI Systems, *Applications of Artificial Intelligence II*", Proc. SPIE 548, 1985, pp. 249-257.

Parker, D.B., "Learning Logic", *Invention Report, 581-64, File 1, Office of Technology Licensing*, Stanford University, Oct, 1982.

Parker, D.B., "Learning Logic", *TR-47, Center for Computational Research in Economics and Management Science*, MIT, April, 1985.

Psaltis, D. and Abu-Mostafa, Y.S, "Computation Power of Parallelism in Optical Computers", California Institute of Technology", 1985.

Psaltis, D. and Farhat, N., "Optical Information Processing Based on an Associative-Memory Model of Neural Nets with Thresholding and Feedback", *Optics Letters*, Vol. 11, Feb, 1985, pp.118-120.

Rescorla, R.A. and Wagner, A.R., "A Theory of Pavlovian Conditioning: Variations in the Effectiveness of Reinforcement and Non-Reinforcement", In Black, A.H. and Prokasy, W.F. Eds., *Classical Conditioning II: Current Research and Theory*, Appleton-Century-Crofts, New York,1972.

Rosenblatt, F., *"Principles of Neurodynamics"*, Spartan Books, Washington, 1962.

Rumelhart, D.E., Hinton G.E., and Williams, R.J., "Learning Internal Representations by Error Propagation", *Institute for Cognitive Science Report 8506*, UCSD, Sept,1985.

Rumelhart, D.E., McClelland, J.L., eds., *"Parallel Distributed Processing", I & II*, Cambridge: MIT Press, 1986.

Sivilotti, M., Emerling, M., and Mead, C., "A Novel Associative Memory Implemented Using Collective Computation", *Proc. Chapel Hill Conference on VLSI*, 1985.

Soffer, B.H., Dunning, G.J., Owechko, Y., and Maron, E., "Associative Holographic Memory with Feedback Use Phase-Conjugate Mirrors", *Optics Letters*, 11, Feb, 1986, pp. 118-120.

von der Marlsburg, C., "Self Organization of Orientation Sensitive Cells in the Striate Cortex", *Kybernetik*, Vol. 14, 1973, pp. 85-100.

Widrow, B., "Generalization and Information Storage in Networks of Adaline "Neurons"", In Yovits, M., Jacobi, G., and Goldstein, G., Eds., *Self-organization systems*, Spartan Books, 1962, pp. 435-461.

Widrow, B., *"Adaptive Signal Processing"*, Prentice-Hall,Inc., Englewood Cliff, N.J., 1985.

Wilshaw, D.J., *"Models of Distributed Associative Memories"*, Ph.D. Thesis, University of Edinburgh, 1971.

Wilshaw, D.J. and Longuet-Higgins, H.C., " Associative Memory Models", in B. Meltzer and O. Michie Eds., *Machine Intelligence*, Edinburgh: Edinburgh University Press, 1971.