was found over sound input alone at signal-to-noise ratios below 15 dB.

The previous applications have used mostly neurons that distort sums of products. The seventh article, "Neural Networks for Switching," by Timothy X Brown of the California Institute of Technology, shows how neural networks with inhibition (same term used in biology and engineering) can be applied to a central function of common-carrier communication, that of finding or assigning a path through a switch. This is an example of an optimization or assignment problem at which neural networks, natural and synthetic, have been found to be useful. The particular switch studied here is a rearrangeable switch, but the general nonlayered architecture that makes heavy use of inhibitory connections, as natural neural networks often do, is more broadly applicable to switching and routing. Other communications applications of the inhibitory architecture could be found in communication routing problems, such as call routing or packet routing in wide-area networks, bandwidth allocation in space and ground networks, and frequency assignment or reassignment in cellular radio. The article builds on the earlier work of M. C. Paull and D. Slepian on call rearrangement, 25 or more years ago, but neural networks were not part of these early algorithms.

The eighth and final article, "Defense Applications of Neural Networks," by Jasper Lupo of the Defense Advanced Research Projects Agency (DARPA), shows how neural networks can help provide functions such as machine vision, speech recognition, and data structuring for efficient utilization by humans. These are operations which occur in many places in the national defense in sensing and communication systems. The computational capabilities of living creatures, of neural network simulators, and of potential special-purpose neural hardware are reviewed, with projected technological capabilities. Potential applications of neural networks to high data-rate sensors in the national defense are presented with figures and estimated requirements on interconnects and interconnects/second. These applications motivated the new DARPA program in neural networks.

The eight articles, all invited by the Guest Editor, were also all refereed. I thank the referees, who are listed here in alphabetical order: Philip Alvelda, Pierre Baldi, Allen Gersho, Rodney M. Goodman, Fernando Pineda, Jawad Salehi, Bernard H. Soffer, and Eyal Yair. Thanks are also due to Stephen B. Weinstein, who suggested this special issue, and to Carol M. Lof, publisher of IEEE COMMUNICATIONS MAGAZINE, who ably handled the marked-up submissions. The work of the Guest Editor for this issue was supported by NASA and Pacific Bell.

Neural Networks for Circuits and Systems

NEVINE EL-LEITHY AND ROBERT W. NEWCOMB,[1] FELLOW, IEEE

Abstract—This letter summarizes material from 16 papers on neural networks from the May 1989 special issue of IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS.

The purpose of this letter is to let readers know about the special issue on neural networks published in the May 1989 IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS.[2] The issue contains the following papers.

1) M. A. C. Maher, S. P. DeWeerth, M. A. Mahawold, and C. A. Mead, "Implementing Neural Architectures Using Analog VLSI Circuits," pp. 643–652. This paper discusses a methodology for building artificial neural networks in CMOS VLSI.

2) D. K. Hartline, "Simulation of Restricted Neural Networks with Reprogrammable Neurons," pp. 653–660. Network models for the SYNETSIM program are presented, these being based upon electrobiochemical data.

3) G. Mirchandani and W. Cao, "On Hidden Nodes for Neural Nets," pp. 661–664. A proof is given that the maximum number of separable regions of the input space is a function of both the number of hidden nodes and the input space dimension.

4) M. L. Brady, R. Raghaven, and J. Slawny, "Back Propagation Fails to Separate Where Perceptrons Succeed," pp. 665–674. Counterexamples are presented to show that the limitations of perceptrons are not overcome by the back propagation algorithm.

5) D. L. Standley and J. L. Wyatt, Jr., "Stability Criterion for Lateral Inhibition and Related Networks that is Robust in the Presence of Integrated Circuit Parasitics," pp. 675–681. A design approach is presented which guarantees that lateral inhibition networks will remain stable in the presence of parasitics.

6) A. R. Stubberud and R. J. Thomas, "Associative Recall Using a Contraction Operator," pp. 682–686. An associative memory transformation is introduced which has rapid convergence, noise rejection, and some learning.

7) N. J. Dimopoulos, "A Study of the Asymptotic Behavior of Neural Networks," pp. 687–694. Neural network nonlinear differential equations are discussed and topologies, including cerebellum type, are established which exhibit asymptotic behavior.

8) A. D. Culhane, M. C. Peckerar, and C. R. K. Marrian, "A Neural Net Approach to Discrete Hartley and Fourier Transforms," pp. 695–703. An electronic circuit based on a multiply connected neural net is presented to compute the discrete Hartley and Fourier transforms.

9) O. K. Ersoy and C.-H. Chen, "Learning of Fast Transforms and Spectral Domain Neural Computing," pp. 704–712. The interaction between neural networks and fast transforms is presented with emphasis upon the use of learning algorithms.

10) J.-H. Li, A. N. Michel, and W. Porod, "Analysis and Synthesis of a Class of Neural Networks: Variable Structure Systems with Infinite Gain," pp. 713–731. The theory of ordinary differential equations with discontinuities is used to set up analysis and design procedures for neural networks with infinite gain.

11) D. E. Van den Bout and T. K. Miller, III, "A Digital Architecture Employing Stochasticism for the Simulation of Hopfield Neural Nets," pp. 732–738. A digital architecture which uses stochastic logic for simulating the behavior of Hopfield neural networks is described.

12) M. K. Habib and H. Akel, "A Digital Neuron-Type Processor and Its VLSI Design," pp. 739–746. A set of neuron-type circuit elements based on logic gate circuits with multi-input multi-fan output capability and realizable in VLSI is presented.

13) K. A. Boahen, P. O. Pouliquen, A. G. Andreou, and, R. E. Jenkins, "A Heteroassociative Memory Using Current-Mode MOS Analog VLSI Circuits," pp. 747–755. Use is made of analog current-mode circuits operating in subthreshold conduction to achieve a scalable architecture for the implementation of neural networks with low power consumption.

14) B. Linares-Barranco, E. Sánchez-Sinencio, A. Rodríguez-Vázquez, and J. L. Huertas, "A Programmable Neural Oscillator Cell," pp. 756–761. Using operational transconductance amplifiers a programmable neural oscillator based upon hysteresis is presented.

15) M. Verleysen, B. Sirletti, A. Vandemeulebroecke, and P. G. A. Jespers, "A High-Storage Capacity Content-Addressable

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[1] N. El-Leithy and R. W. Newcomb were Guest Editors of the Special Issue on Neural Networks, IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS, May 1989.

[2] *IEEE Trans. Circuits Syst.*, vol. 36, no. 5, May 1989.

Memory and Its Learning Algorithm," pp. 762–766. Using CMOS technology a VLSI fully interconnected neural network is realized with only two binary memory points per synapse.

16) R. D. Reed and R. L. Geiger, "A Multiple-Input OTA Circuit for Neural Networks," pp. 767–770. A multiple input operational transconductance amplifier suitable for VLSI is presented that models neurons with voltage adjustable weights.

Neural Networks for Control Systems

PANOS J. ANTSAKLIS, SENIOR MEMBER, IEEE

Abstract—**This letter summarizes five papers on neural networks from the April 1989 special section of the IEEE CONTROL SYSTEMS MAGAZINE.**

The April 1989 issue of the IEEE CONTROL SYSTEMS MAGAZINE (CSM) contained five papers in a special section on neural networks for control systems.[1] This was the second special section of papers on neural networks presented in the CSM, the first appearing in April 1988. This collection of papers has generated significant interest in the use of neural networks in control and a CSM special issue devoted to neural networks for control systems is planned for April 1990 (P. J. Antsaklis is the Guest Editor of this special issue). Neural networks apparently offer great potential and promise, and there is hope in the control community of being able to achieve control objectives which have not been attained before. Time, of course, will tell, as the pertinent issues are complex and the basic questions of how neural networks can be best utilized in control problems are not completely settled.

The first paper on neural networks in the April 1989 issue, by M. Kuperstein and J. Rubinstein, uses visual information and learning to control a robot arm so that it grasps objects in space. The classic control problem of the inverted pendulum is revisited in the next paper, by C. W. Anderson, with the new twist that performance information is severely limited; a neural network learns how to balance the pendulum. In the third paper (H. Liu *et al.*), a neural network is used to learn the map between object primitives and grasp modes in the development of a generic architecture for robot hand control; learning here is desirable, as the map is rather complex and "it is better learned than fully detailed out." In the fourth paper, K. Passino *et al.* use a multilayer perceptron to classify numeric data and assign appropriate symbols to various classes; these symbols are then used in symbolic controllers which provide intelligent, higher level control of continuous variable dynamic systems. The last paper by R. Eckmiller, deals with managing trajectories or space–time functions using a method called a neural triangular lattice; in contrast to previous papers, explicit reference is made here to biological nervous systems.

The articles are discussed in more detail below.

Learning to achieve sensory-motor coordination is the subject of M. Kuperstein and J. Rubinstein's article, "Implementation of an Adaptive Neural Controller for Sensory Motor Coordination" (pp. 25–30). An adaptive neural controller is developed here and it is used to control a multijoint arm to reach objects in space. The controller can learn, unsupervised, to accurately grasp an elongated object arbitrarily positioned in space. No *a priori* knowledge of the robotic arm dynamics is assumed. Two cameras provide sensory feedback and the neural controller learns the appropriate control actions by associating arm positions and camera views or, more precisely, arm motor signals and object images. The controller is then physically implemented using a five-degree-of-freedom arm, stereo cameras, and a commercial image processing system.

C. W. Anderson, in "Learning to Control an Inverted Pendulum using Neural Networks" (pp. 31–37), addresses the rather famous control problem of balancing an inverted pendulum, or a broomstick, hinged on a cart and allowed to move only within the vertical plane; control is exercised by moving the cart. Conventional control solutions of this problem do exist and the inverted pendulum experiment has been used for a long time by many to graphically demonstrate and convince the nonbeliever of the awesome powers of control theory! Controlling the inverted pendulum was also one of the early control applications of neural networks, over 25 years ago. The novelty here is that, in addition to having no *a priori* knowledge of the dynamics of the cart and the pendulum, performance feedback is assumed to be unavailable at each step; it appears only as a positive signal when the pendulum falls or reaches the bounds of the track. Learning methods using reinforcement and temporal differences are used to build the necessary knowledge base and balance the pendulum for extended time periods.

H. Liu, T. Iberall, and G. Bekey, in "Neural Network Architecture for Robot Hand Control" (pp. 38–43), describe a generic architecture for robot hand control and focus on the relationship between object primitives and group modes such as "power grasp," "chuck grip," and "pulp pinch" among others. Device independent, generic robot hand controllers of the type described in this paper are of increasing importance and interest as various dextrous robot hands are designed and built; this is because such architectures will allow the low-level control problems associated with a particular robot hand to be separated from high-level functionality. Because the complex relationship between object primitives and group modes is better learned than fully detailed out, the learning capabilities of neural networks are invoked to compute the relationship.

K. Passino, M. Sartori, and P. J. Antsaklis use a multilayer perceptron in the next paper titled "Neural Computing for Numeric-to-Symbolic Conversion in Control Systems" (pp. 44–52), to classify numeric data and assign appropriate symbols to various classes. This procedure, similar to data reduction in pattern recognition, extracts the necessary information from the data so it can be used by a symbol processing controller. Such controllers provide the higher level decision making necessary in the "intelligent" control of processes. The use of this numeric-to-symbolic converter is described in the case of a discrete event system acting as a controller of a continuous variable dynamic system, here a water tank; it is also shown how it can implement fault trees which provide useful information, alarms, in a biological system and information for failure diagnosis and control purposes in an aircraft.

The management of trajectories is the topic of the final paper by R. Eckmiller in "Neural Nets for Sensory and Motor Trajectories" (pp. 53–59). In contrast to the previous papers, explicit and extensive references to biological systems are made to gain understanding for the development of intelligent robots. In particular, one major aspect of information processing in biological nervous systems is emphasized and discussed, namely the management of trajectories or space–time functions, and a novel approach to the problem using artificial neural nets is presented. In this approach, the space–time functions representing the trajectories are separated so that the spatial parameters are stored in one neural map, while the time parameters are in another, and a method called neural triangular lattice is suggested for implementing the neural maps.

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[1] *IEEE Control Syst. Mag.*, vol. 9, no. 3, special section pp. 25–59, Apr. 1989.

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