Optoelectronic Neural Networks and Learning Machines

Nabil H. Farhat

Foreword

Circuits and Devices Magazine is featuring three sequential articles on the current status of artificial neural network implementation technology. The current offering, on optronic implementation of artificial neural networks, is the second entry in this trilogy. It is sandwiched between the previous overview on analog implementation and the upcoming survey of digital artificial neural networks.

Nabil H. Farhat, who penned this overview, is a co-author of the 1985 article in Optics Letters and follow-up paper in Applied Optics that broke ground for modern optical implementation of artificial neural networks.

Robert J. Marks II

Abstract

Optics offers advantages in realizing the parallelism, massive interconnectivity, and plasticity required in the design and construction of large-scale optoelectronic (photonic) neurocomputers that solve optimization problems at potentially very high speeds by learning to perform mappings and associations. To elucidate these advantages, a brief neural net primer based on phase-space and energy landscape considerations is first presented. This provides the basis for subsequent discussion of optoelectronic architectures and implementations with self-organization and learning ability that are configured around an optical crossbar interconnect. Stochastic learning in the context of a Boltzmann machine is then described to illustrate the flexibility of optoelectronics in performing tasks that may be difficult for electronics alone. Stochastic nets are studied to gain insight into the possible role of noise in biological neural nets. We close by describing two approaches to realizing large-scale optoelectronic neurocomputers: integrated optoelectronic neural chips with interchip optical interconnects that enables their clustering into large neural networks, and nets with two-dimensional rather than one-dimensional arrangement of neurons and four-dimensional connectivity matrices for increased packing density and compatibility with two-dimensional data. We foresee integrated optoelectronics or photonics playing an increasing role in the construction of a new generation of versatile programmable analog computers that perform computations collectively for use in neuromorphic (brain-like) processing and fast simulation and study of complex nonlinear dynamical systems.

Introduction

Neural net models and their analogs offer a brain-like approach to information processing and representation that is distributed, nonlinear and iterative. Therefore they are best described in terms of phase-space behavior where one can draw upon a rich background of theoretical results developed in the field of nonlinear dynamical systems. The ultimate purpose of biological neural nets (BNNs) is to sustain and enhance survivability of the organism they reside in, doing so in an imprecise and usually very complex environment where sensory impressions are at best sketchy and difficult to make sense of had they been treated and analyzed by conventional means. Embedding artificial neural nets (ANNs) in man-made systems endows them therefore with enhanced survivability through fault-tolerance, robustness and speed. Furthermore, survivability implies adaptability through self-organization, knowledge accumulation and learning. It also implies lethality.

All of these are concepts found at play in a wide range of disciplines such as economics, social science, and even military science which can perhaps explain the widespread interest in neural nets exhibited today from both intellectual and technological viewpoints. It is widely believed that artificial neurocomputing and knowledge processing systems could eventually have significant impact on information processing, pattern recognition, and control. However, to realize the potential advantages of neuromorphic processing, one must contend with the issue of how to carry out collective neural computation algorithms at speeds far beyond those possible with digital computing. Obviously parallelism and concurrency are essential ingredients and one must contend with basic implementation issues of how to achieve such massive connectivity and parallelism and how to achieve artificial plasticity, i.e., adaptive modification of the strength of interconnections (synaptic weights) between neurons that is needed for memory and self-programming (self-organization and learning). The answers to these questions seem to be coming from two directions of research. One is connection machines in which a large number of digital central processing units are interconnected to perform parallel computations in VLSI hardware; the other is analog hardware where a large number of simple processing units (neurons) are connected through modifiable weights such that their phase-space dynamic behavior has useful signal processing functions associated with it.

Analog optoelectronic hardware implementation of neural nets (see Farhat et al. in list of further reading), since first introduced in 1985, has been the focus of attention for several reasons. Primary among these is that the optoelectronic or photonic approach combines the best of two worlds: the massive interconnectivity and parallelism of optics and the flexibility, high gain, and decision making capability (nonlinearity) offered by electronics. Ultimately, it seems more attractive to form analog neural hardware by completely optical means where switching of signals from optical to electronic carriers and vice versa is avoided. However, in the absence of suitable fully optical decision making devices (e.g., sensitive optical bistability devices), the capabilities

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of the optoelectronic approach remain quite attractive and could in fact remain competitive with other approaches when one considers the flexibility of architectures possible with it.* In this paper we concentrate therefore on the optoelectronic approach and give selected examples of possible architectures, methodologies and capabilities aimed at providing an appreciation of its potential in building a new generation of programmable analog computers suitable for the study of non-linear dynamical systems and the implementation of mappings, associative memory, learning, and optimization functions at potentially very high speed.

We begin with a brief neural net primer that emphasizes phase-space description, then focus attention on the role of optoelectronics in achieving massive interconnectivity and plasticity. Architectures, methodologies, and suitable technologies for realizing optoelectronic neural nets based on optical crossbar (matrix vector multiplier) configurations for associative memory function are then discussed. Next, partitioning an optoelectronic analog of a neural net into distinct layers with a prescribed interconnectivity pattern as a prerequisite for self-organization and learning is discussed. Here the emphasis will be on stochastic learning by simulated annealing in a Boltzmann machine. Stochastic learning is of interest because of its relevance to the role of noise in biological neural nets and because it provides an example of a task that demonstrates the versatility of optics. We close by describing several approaches to realizing the large-scale networks that would be required in analog solution of practical problems.

Neural Nets—A Brief Overview

In this section, a brief qualitative description of neural net properties is given. The emphasis is on energy landscape and phase-space representations and behavior. The descriptive approach adopted is judged best as background for appreciating the material in subsequent sections without having to get involved in elaborate mathematical exposition. All neural net properties described here are well known and can easily be found in the literature. The viewpoint of relating all neural net properties to energy landscape and phase-space behavior is also important and useful in their classification.

A neural net of N neurons has $(N^2\text{-}N)$ interconnections or $(N^2\text{-}N)/2$ symmetric interconnections, assuming that a neuron does not communicate with itself. The state of a neuron in the net, i.e., its firing rate, can be taken to be binary (0, 1) (on-off, firing or not firing) or smoothly varying according to a nonlinear continuous monotonic function often taken as a sigmoidal function bounded from above and below. Thus the state of the i-th neuron in the net can be described mathematically by

$$s_i = f\{u_i\} \qquad i = 1, 2, 3 \ldots N^{**} \tag{1}$$

where $f\{.\}$ is a sigmoidal function and

$$u_i = \sum_{j \neq i}^{N} W_{ij} s_j - \theta_i + I_i \tag{2}$$

is the activation potential of the i-th neuron, W_{ij} is the strength or weight of the synaptic interconnection between the j-th neuron and the i-th neuron, and $W_{ii} = 0$(i.e., neurons do not talk to themselves). θ_i and I_i are, respectively, the threshold level and external or control input to the i-th neuron, thus $W_{ij}S_j$ represents the input to neuron i from neuron j and the first term on the right side of (2) represents the sum of all such inputs to the i-th neuron. For excitatory interconnections or synapses, W_{ij} is positive, and it is negative for inhibitory ones. For a binary neural net, that is, one in which the nurons are binary, i.e., $s_i[0,1]$, the smoothly varying function $f\{.\}$ is replaced by $U\{.\}$, where U is the unit step function. When W_{ij} is symmetric, i.e., $W_{ij} = W_{ji}$, one can define (see J. J. Hopfield's article in list of further reading) a Hamiltonian or energy function E for the net by

$$E = -\frac{1}{2}\sum_i u_i s_i$$

$$= -\frac{1}{2}\sum_i \sum_j W_{ij} s_i s_j - \frac{1}{2}\sum_i (\theta_i - I_i) s_i \tag{3}$$

The energy is thus determined by the connectivity matrix W_{ij}, the threshold level θ_i and the external input I_i. For symmetric W_{ij} the net is stable; that is, for any threshold level θ_i and given "strobed" (momentarily applied) input I_i, the energy of the net will be a decreasing function of the neurons state s_i of the net or a constant. This means that the net always heads to a steady state of local or global energy minimum. The descent to an energy minimum takes place by the iterative discrete dynamical process described by Eqs. (1) and (2) regardless of whether the state update of the neurons is synchronous or asynchronous. The minimum can be local or global, as the "energy landscape" of a net (a visualization of E for every state s_i) is not monotonic but will possess many uneven hills and troughs and is therefore characterized by many local minima of various depths and one global (deepest) minimum. The energy landscape can therefore be modified in accordance with Eq. (3) by changing the interconnection weights W_{ij} and/or the threshold levels θ_i and/or the external input I_i. This ability to "sculpt" the energy landscape of the net provides for almost all the rich and fascinating behavior of neural nets and for the ongoing efforts of harnessing these properties to perform sophisticated spatio-temporal mappings, computations, and control functions. Recipes exist that show how to compute the W_{ij} matrix to make the local energy minima correspond to specific desired states of the network. As the energy minima are stable states, the net tends to settle in one of them, depending on the initializing state, when strobed by a given input. For example, a binary net of $N = 3$ neurons will have a total of $2^N = 8$ states. These are listed in Table 1. They represent all possible combinations s_1, s_2 and s_3 of the three neurons that describe the state vector $s = [s_1, s_2, s_3]$ of the net. For a net of N neurons the state vector is N-dimensional. For $N = 3$ the state vector can be represented as a point (tip of a position vector) in 3-D

*It is worth mentioning here that recent results obtained in our work show that networks of logistic neurons, whose response resembles that of the derivative of a sigmoidal function, exhibit rich and interesting dynamics, including spurious state-free associative recall, and allow the use of unipolar synaptic weights. The networks can be realized in a large number of neurons when implemented with optically addressed reflection-type liquid crystal spatial light modulators. However, the flexibility of such an approach versus that of the photonic approach is yet to be determined.

**From here on it will be taken as understood that whenever the subscripts (i or j) appear, they run from 1 up to N where N is the number of neurons in the net.

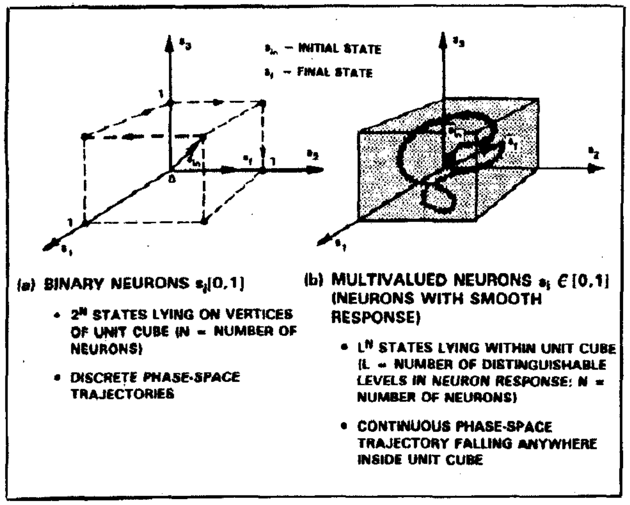

Fig. 1 Phase-space or state space representation and trajectories for a neural net of N = 3 neurons. (a) for binary neurons, (b) for neurons with normalized smooth (sigmoidal) response.

space. The eight state vectors listed in Table I fall then on the vertices of a unit cube as illustrated in Fig. 1(a). As the net changes its state, the tip of the state vector jumps from vertex to vertex describing a discrete trajectory as depicted by the broken trajectory starting from the tip of the initializing state vector $\mathbf{s}_i$ and ending at the tip of the final state vector $\mathbf{s}_f$. For any symmetric connectivity matrix assumed for the three-neuron net example, each of the eight states in Table I yields a value of the energy E. A listing of these values for each state represents the energy landscape of the net.

For a nonbinary neural net whose neurons have normalized sigmoidal response $s_i \epsilon [0,1]$, i.e., s_i varies smoothly between zero and one, the phase-space trajectory is continuous and is always contained within the unit cube as illustrated in Fig. 1(b). The neural net is governed then by a set of continuous differential equations rather than the discrete update relations of Eqs. (1) and (2). Thus one can talk of nets with either discrete or continuous dynamics. The above phase-space representation is extendable to a neural net of N neurons where one considers discrete trajectories between the vertices of a unit hypercube in N-dimensional space or a smooth trajectory confined within the unit hypercube for discrete and continuous neural nets, respectively.

The stable states of the net, described before as minima of the energy landscape, correspond to points in the phase-space towards which the state of the net tends to evolve in

Table I. Possible States of a Binary Neural Net of 3 Neurons

s_1	s_2	s_3
0	0	0
0	0	1
0	1	0
1	0	0
0	0	1
1	0	1
1	1	0
1	1	1

time when the net is iterated from an arbitrary initial state. Such stable points are called "attractors" or "limit points" of the net, to borrow from terms used in the description of nonlinear dynamical systems. Attractors in phase-space are characterized by basins of attraction of given size and shape. Initializing the net from a state falling within the basin of attraction of a given attractor and thus regarded as an incomplete or noisy version of the attractor, leads to a trajectory that converges to that attractor. This is a many to one mapping or an associative search operation that leads to an associative memory attribute of neural nets.

Local minima in an energy landscape or attractors in phase-space can be fixed by forming W_{ij} in accordance with the Hebbian learning rule (see both Hebb and Hopfield in list of further reading), i.e., by taking the sum of the outer products of the bipolar versions of the state vector we wish to store in the net

$$W_{ij} = \sum_{m=1}^{M} v_i^{(m)} v_j^{(m)} \tag{4}$$

where

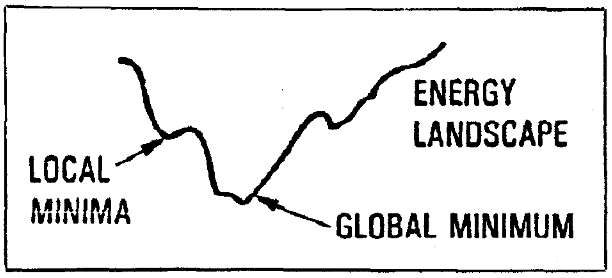

Fig. 2 Conceptual representation of energy landscape.

$$v_i^{(m)} = 2s_i^{(m)} - 1 \qquad i = 1,2\ldots N \qquad m = 1,2\ldots M \tag{5}$$

are M bipolar binary N-vectors we wish to store in the net. Provided that $s_i^{(m)}$ are uncorrelated and

$$M \leq \frac{N}{4\ell nN} \tag{6}$$

the M stored state $s^{(m)}$ will become attractors in phase-space of the net or equivalently their associated energies will be local minima in the energy landscape of the net as illustrated conceptually in Fig. 2. As M increases beyond the value given by (6), the memory is overloaded, spurious local minima are created in addition to the desired ones and the probability of correct recall from partial or noisy information deteriorates, compromising operation of the net as an associative memory (see R.J. McEliece et al. in list of further reading).

The net can also be formed in such a way as to lead to a hetero-associative storage and recall function by setting the interconnection weights in accordance with

$$W_{ij} = \sum_{m} v_i^{(m)} g_j^{(m)} \tag{7}$$

where $\bar{v}^{(m)}$ and $\bar{g}^{(m)}$ are associated N-vectors. Networks of this variety can be used as feedforward networks only and this precludes the rich dynamics encountered in feedback or recurrent networks from being observed. Nevertheless, they are useful for simple mapping and representation.

Energy landscape considerations are useful in devising formulas for the storage of sequences of associations or a cyclic sequence of associations as would be required for conducting sequential or cyclic searches of memories.

Learning in biological neural nets is thought to occur by self-organization where the synaptic weights are modified electrochemically as a result of environmental (sensory and other (e.g., contextual)) inputs. All such learning requires plasticity, the process of gradual synaptic modification. Adaptive learning algorithms can be deterministic or stochastic; supervised or unsupervised. An optoelectronic (Boltzmann machine) and its learning performance will be described in the section on large scale networks as an illustration of the unique capabilities of optoelectronic hardware.

Neural Nets Classification and Useful Functions

The energy function and energy landscape description of the behavior of neural networks presented in the preceding sections allows their classification into three groups. For one group the local minima in the energy landscape are what counts in the network's operation. In the second group the local minima are not utilized and only the global minimum is meaningful. In the third group the operations involved do not require energy considerations. They are merely used for mapping and reduction of dimensionality. The first group includes Hopfield-type nets for all types of associative memory applications that include auto-associative, hetero-associative, sequential and cyclic data storage and recall. This category also includes all self-organizing and learning networks regardless of whether the learning in them is supervised, unsupervised, deterministic, or stochastic as the ultimate result of the fact that learning, whether hard or soft, can be interpreted as shaping the energy landscape of the net so as to "dig" in it valleys corresponding to learned states of the network. All nets in this category are capable of generalization. An input that was not learned specifically but is within a prescribed Hamming distance* to one of the entities learned would elicit, in the absence of any contradictory information, an output that is close to the outputs evoked when the learned entity is applied to the net. Because of the multilayered and partially interconnected nature of self-organizing networks, one can define input and output groups of neurons that can be of unequal number (See section on large scale networks). This is in contrast to Hopfield-type nets which are fully interconnected and therefore the number of input and output neurons is the same (the same neurons define the initial and final states of the net). The ability to define input and output groups of neurons in multilayered nets enables additional capabilities that include learning, coding, mapping, and reduction of dimensionality.

The second group of neural nets includes nets that perform calculations that require finding the global energy minimum of the net. The need for this type of calculation

*The Hamming distance between two binary N-vectors is the number of elements in which they differ.

**A chaotic attractor is manifested by a phase-space trajectory that is completely unpredictable and is highly sensitive to initial conditions. It could ultimately turn out to play a role in cognition.

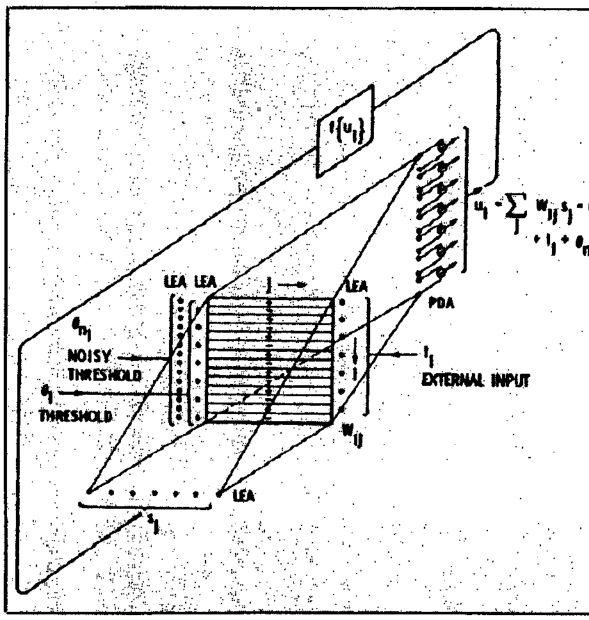

Fig. 3 Optoelectronic analog circuit of a fully interconnected neural net.

often occurs in combinatorial optimization problems and in the solution of inverse problems encountered, for example, in vision, remote sensing, and control.

The third group of neural nets is multilayered with localized nonglobal connections similar to those in cellular automata where each neuron communicates within its layer with a pattern of neurons in its neighborhood and with a pattern of neurons in the next adjacent layer. Multilayered nets with such localized connections can be used for mapping and feature extraction. Neural nets can also be categorized by whether they are single layered or multilayered, self-organizing or nonself-organizing, solely feedforward or involve feedback, stochastic or deterministic. However, the most general categorization appears to be in terms of the way the energy landscape is utilized, or in terms of the kind of attractors formed and utilized in its phase-space (limit points, limit cycles, or chaotic**).

Implementations

The earliest optoelectronic neurocomputer was of the fully interconnected variety where all neurons could talk to each other. It made use of incoherent light to avoid interference effects and speckle noise and also relax the stringent alignment required in coherent light systems. An optical crossbar interconnect (see Fig. 3) was employed to carry out the vector matrix multiplication operation required in the summation term in Eq. 2. (see Farhat et al. (1985) in list of further reading). In this arrangement the state vector of the net is represented by the linear light emitting array (LEA) or equivalently by a linear array of light modulating elements of a spatial light modulator (SLM), the connectivity matrix W_{ij} is implemented in a photographic transparency mask (or a 2-D SLM when a modifiable connectivity mask is needed for adaptive learning), and the activation potential u_i is measured with a photodiode array (PDA). Light from the LEA is smeared vertically onto the W_{ij} mask with

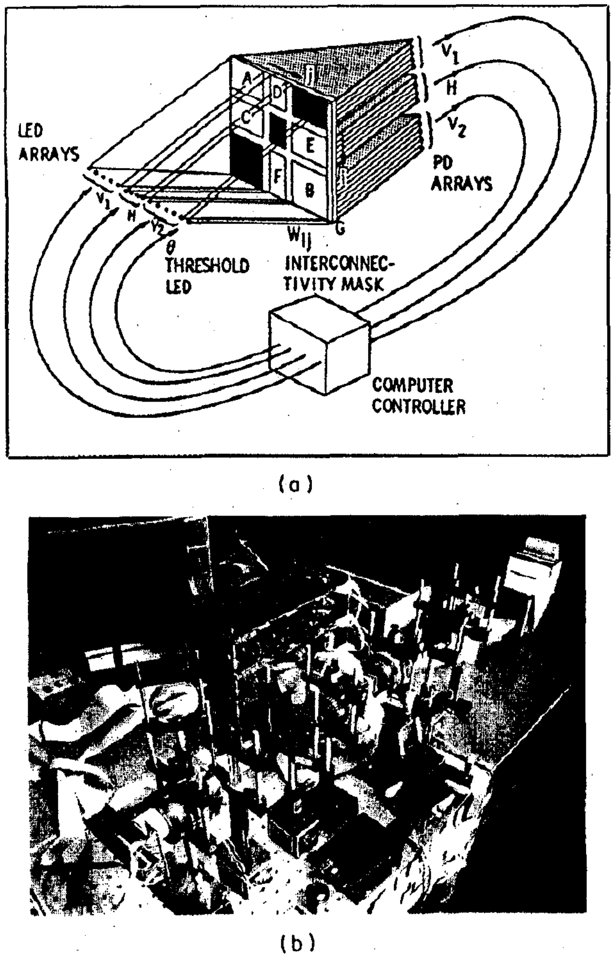

Fig. 4 Boltzmann learning machine. (a) optoelectronic circuit diagram of a net partitioned into three layers by blocking segments of the interconnectivity mask, (b) hardware implementation showing the state vector LED array at the top right, the MOSLM at the center (between lenses) and an intensified PDA (PDA abutted to an image intensifier fiber output window for added gain) in the lower left. The integrated circuit board rack contains the MOSLM driver and computer interface and the TV receiver in the background provides the "snow pattern" that is imaged through a slit onto the intensifier input window for optical injection of noise in the network.

the aid of an anamorphic lens system (cylindrical and spherical lenses in tandem not shown in the figure for simplicity). Light passing through rows of W_{ij} is focused onto the PDA elements by another anamorphic lens system. To realize bipolar transmission values in incoherent light, positive elements and negative elements of any row of W_{ij} are assigned to two separate subrows of the mask and light passing through each subrow is focused onto adjacent pairs of photosites of the PDA whose outputs are subtracted. In Fig. 3, both the neuron threshold θ_i and external input I_i are injected optically with the aid of a pair of LEAs whose light is focused on the PDA. Note that positive valued I_i is assumed here and therefore its LEA elements are shown positioned to focus onto positive photosites of the PDA only.

This architecture was successfully employed in the first implementation of a 32 neuron net (see Farhat et al. (1985) in list of further reading). Fig. 3 also shows a third LEA for injection of spatio-temporal noise into the net as would be required, for example, in the implementation of a noisy threshold scheme for the Boltzmann learning machine to be discussed later. The net of Fig. 3 behaved as an associative memory very much as expected and was found to exhibit correct recovery of three neurons stored from partial information and showed robustness with element failure (two of its 32 neurons were accidentally disabled, 2 PDA elements broke, and no noticeable degradation in performance was observed).

In the arrangement of Fig. 3, the neurons are fully interconnected. To implement learning in a neural net, one needs to impart structure to the net, i.e., be able to partition the net into distinct input, output, and hidden groups or layers of neurons with a prescribed pattern of communication or interconnections between them which is not possible in a fully interconnected or single layer network. A simple but effective way of partitioning a fully interconnected optoelectronic net into several layers to form a partially interconnected net is shown in Fig. 4(a). This is done simply by blocking certain portions of the W_{ij} matrix.

In the example shown, the blocked submatrices serve to prevent neurons from the input group V_1 and the output group V_2 from talking to each other directly. They can do so only via the hidden or buffer group of neurons H. Furthermore, neurons within H can not talk to each other. This partition scheme enables arbitrary division of neurons among layers and can be rapidly set when a programmable nonvolatile SLM under computer control is used to implement the connectivity weights. Neurons in the input and output groups are called visible neurons because they interface with the environment.

The architecture of Fig. 4 can be used in supervised learning where, beginning from an arbitrary W_{ij}, the net is presented with an input vector from the training set of vectors it is required to learn through V_1 and its convergent output state is observed on V_2 and compared with the desired output (association) to produce an error signal which is used in turn according to a prescribed formula to update the weights matrix. This process of error-driven adaptive weights modification is repeated a sufficient number of times for each vector and all vectors of the training set until inputs evoke the correct desired output or association at the output. At that time the net can be declared as having captured the underlying structure of the environment (the vectors presented to it) by forming an internal representation of the rules governing the mappings of inputs into the required output associations.

Many error-driven learning algorithms have been proposed and studied. The most widely used, the error back-projection algorithm (see Werbos, Parker, and Rumelhart et al. in list of further reading), is suited for use in feed forward multilayered nets that are void of feedback between the neurons. The architecture of Fig. 4(a) has been successfully employed in the initial demonstration of supervised stochastic learning by simulated annealing. Our interest in stochastic learning stemmed from a desire to better understand the possible role of noise in BNNs and to find means for accelerating the simulated annealing process through the use of optics and optoelectronic hardware. For any input-output association clamped on V_1 and V_2 and beginning from an arbitrary W_{ij} that could be random, the net is annealed through the hidden neurons by subjecting them to optically injected noise in the form of a noise component added to the threshold values of the neurons as depicted by θ_{ni} in Fig. 3.

The source of controlled noise used in this implementation was realized by imaging a slice of the familiar "snow pattern" displayed on an empty channel of a television receiver, whose brightness could be varied under computer control, onto the PD array of Fig. 4(a). This produces controlled perturbation or "shaking" of the energy landscape of the net which prevents its getting trapped into a state of local energy minimum during iteration and guarantees its reaching and staying in the state of the global energy minimum or one close to it. This requires that the injected noise intensity be reduced gradually, reaching zero when the state of global energy minimum is reached to ensure that the net will stay in that state. Gradual reduction of noise intensity during this process is equivalent to reducing the "temperature" of the net and is analogous to the annealing of a crystal melt to arrive at a good crystalline structure. It has accordingly been called simulated annealing by early workers in the field.

Finding the global minimum of a "cost" or energy function is a basic operation encountered in the solution of optimization problems and is found not only in stochastic learning. Mapping optimization problems into stochastic nets of this type, combined with fast annealing to find the state of global "cost function" minimum, could be a powerful tool for their solution. The net behaves then as a stochastic dynamical analog computer. In the case considered here, however, optimization through simulated annealing is utilized to obtain and list the convergent states at the end of annealing bursts when the training set of vectors (the desired associations) are clamped to V_1 and V_2. This yields a table or listing of convergent state vectors from which a probability P_{ij} of finding the i-th neuron and the j-th neuron on at the same time is computed. This completes the first phase of learning. The second phase of learning involves clamping the V_1 neurons only and annealing the net through H and V_2, obtaining thereby another list of convergent state vectors at the end of annealing bursts and calculating another probability P'_{ij} of finding the i-th and j-th neurons on at the same time. The connectivity matrix, implemented in a programmable magneto-optic SLM (MOSLM), is modified then by $\Delta W_{ij} = \epsilon(P_{ij} - P'_{ij})$ computed by the computer controller where ϵ is a constant controlling the learning rate. This completes one learning cycle or episode. The above process is repeated again and again until the W_{ij} stabilizes and captures hopefully the underlying structure of the training set. Many learning cycles are required and the learning process can be time-consuming unless the annealing process is sufficiently fast.

We have found that the noisy thresholding scheme leads the net to anneal and find the global energy minimum or one close to it in about 35 time constants of the neurons used. For microsecond neurons this could be 10^4-10^5 times faster than numerical simulation of stochastic learning by simulated annealing which requires random selection of neurons one at a time, switching their states, and accepting the change of state in such a way that changes leading to an energy decrease are accepted and those leading to energy increases are allowed with a certain controlled probability.

The computer controller in Fig. 4 performs several functions. It clamps the input/output neurons to the desired states during the two phases of learning, controls the annealing profile during annealing bursts, monitors the convergent state vectors of the net, and computes and executes the weights modification. For reasons related to the thermodynamical and statistical mechanical interpretation of its operation, the architecture in Fig. 4(a) is called a Boltzmann learning machine. A pictorial view of an optoelectronic (photonic) hardware implementation of a fully operational Boltzmann learning machine is shown in Fig. 4(b). This machine was built around a MOSLM as the adaptive weights mask.

The interconnection matrix update during learning requires small analog modifications ΔW_{ij} in W_{ij}. Pixel transmittance in the MOSLM is binary, however. Therefore a scheme for learning with binary weights was developed and used in which W_{ij} is made 1 if $(P_{ij} - P'_{ij}) > M$ regardless of its preceeding value, where M is a constant, and made -1 if $(P_{ij} - P'_{ij}) < -M$ regardless of its preceeding value, and is left unchanged if $-M \geq (P_{ij} - P'_{ij}) \leq M$. This introduces inertia to weights modification and was found to allow a net of $N = 24$ neuron partitioned into 8-8-8 groups to learn two autoassociations with 95 percent score (probability of correct recall) when the value of M was chosen randomly between (0-.5) for each learning cycle. This score dropped to 70 percent in learning three autoassociations. However, increasing the number of hidden neurons from 8 to 16 was found to yield perfect learning (100 percent score).

Scores were collected after 100 learning cycles by computing probabilities of correct recall of the training set. Fast annealing by the noisy thresholding scheme was found to scale well with size of the net, establishing the viability of constructing larger optoelectronic learning machines. In the following section two schemes for realizing large-scale nets are briefly described. One obvious approach discussed is the clustering of neural modules or chips. This approach requires that neurons in different modules be able to communicate with each other in parallel, if fast simulated annealing by noisy thresholding is to be carried out. This requirement appears to limit the number of neurons per module to the number of interconnects that can be made from it to other modules. This is a thorny issue in VLSI implementation of cascadeable neural chips (see Alspector and Allen in list of further reading). It provides a strong argument in favor of optoelectronic neural modules that have no such limitation because communication between modules is carried out by optical means and not by wire.

Large Scale Networks

To date most optoelectronic implementations of neural networks have been prototype units limited to few tens or hundreds of neurons. Use of neurocomputers in practical applications involving fast learning or solution of optimization problems requires larger nets. An important issue, therefore, is how to construct larger nets with the programmability and flexibility exhibited by the Boltzmann learning machine prototype described. In this section we present two possible approaches to forming large-scale nets as examples demonstrating the viability of the photonic approach. One is based on the concept of a clusterable integrated optoelectronic neural chip or module that can be optically interconnected to form a larger net, and the second is an architecture in which 2-D arrangement of neurons is utilized, instead of the 1-D arrangement described

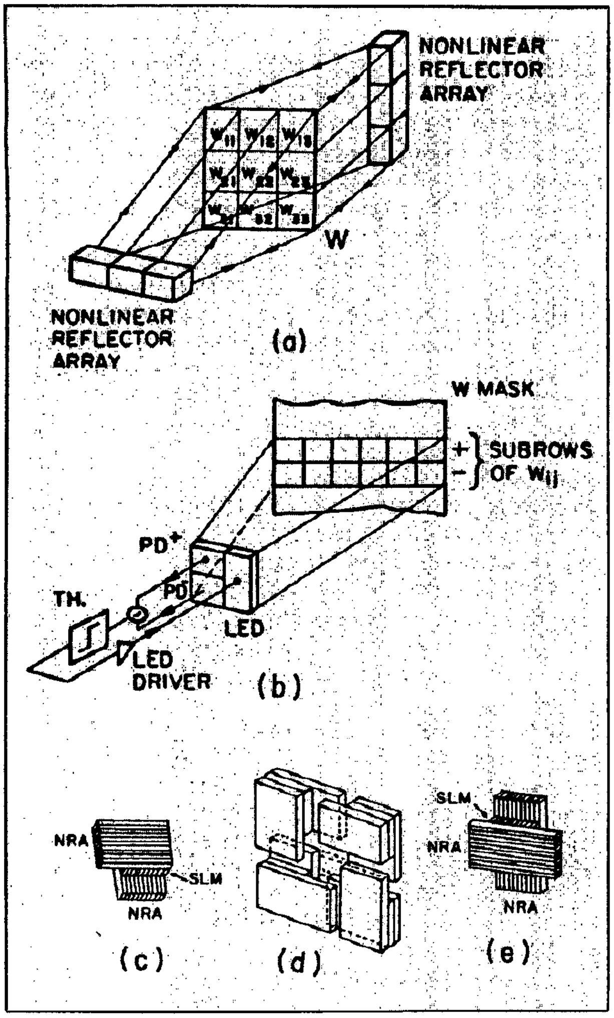

Fig. 5 Optoelectronic neural net employing internal feedback and two orthogonal nonlinear reflector arrays (NRAs) consisting of channels of nonlinear light amplifiers (photodetectors, thresholding amplifiers, LEDs and LED drivers). a) architecture, (b) detail of mask and single element of nonlinear reflector array, (c) and (d) optoelectronic neural chip concept and cluster of four chips, (e) neural chip for forming clusters of more than four chips.

in earlier sections, in order to increase packing density and to provide compatibility with 2-D sensory data formats.

Clusterable Photonic Neural Chips

The concept of a clusterable photonic neural chip, which is being patented by the University of Pennsylvania, is arrived at by noting that when the connectivity matrix is symmetrical, the architectures we described earlier (see Figs. 3 or 4(a)) can be modified to include internal optical feedback and nonlinear "reflection" (optoelectronic detection, amplification, thresholding and light emission or modulation) on both sides of the connectivity mask **W** or nonvolatile SLM (e.g., a MOSLM) as depicted in Fig. 5 (see Farhat (1987) in list of further reading). The nonlinear reflector arrays are basically retro-reflecting optoelectronic or photonic light amplifier arrays that receive and retransmit light on the same side facing the MOSLM.

Two further modifications are needed to arrive at the concept of clusterable integrated optoelectronics or photonic neural chips. One is replacement of the LEDs of the nonlinear reflector arrays by suitable spatial light modulators of the fast ferroelectric liquid crystal variety for example, and extending the elements of the nonlinear reflector arrays to form stripes that extend beyond the dimensions of the connectivity SLM, and sandwiching the latter between two such striped nonlinear reflector arrays oriented orthogonally to each other as depicted in Fig. 5(c). This produces a photonic neural chip that operates in an ambient light environment. Analog integrated circuit (IC) technology would then be used to fabricate channels of nonlinear (thresholding) amplifiers and SLM drivers, one channel for each PD element. The minute IC chip thus fabricated is mounted as an integral part on each PDA/SLM assembly of the nonlinear reflector arrays. Individual channels of the IC chip are bonded to the PDA and SLM elements. Two such analog IC chips are needed per neural chip. The size of the neural chip is determined by the number of pixels in the SLM used.

An example of four such neural chips connected optoelectronically to form a larger net by clustering is shown in Fig. 5(d). This is achieved by simply aligning the ends of the stripe PD elements in one chip with the ends of the stripe SLM elements in the other. It is clear that the hybrid photonic approach to forming the neural chip would ultimately and preferably be replaced by an entirely integrated photonic approach and that neural chips with the slightly different form shown in Fig. 5(e) can be utilized to form clusters of more than four. Large-scale neural nets produced by clustering integrated photonic neural chips have the advantage of enabling any partitioning arrangement, allowing neurons in the partitioned net to communicate with each other in the desired fashion enabling fast annealing by noisy thresholding to be carried out, and of being able to accept both optically injected signals (through the PDAs) or electronically injected signals (through the SLMs) in the nonlinear reflector arrays, facilitating communication with the environment. Such nets are therefore capable of both deterministic or stochastic learning. Computer controlled electronic partitioning and loading and updating of the connectivity weights in the connectivity SLM (which can be of the magneto-optic variety or the nonvolatile ferroelectric liquid crystal (FeLCSLM) variety) is assumed. This approach to realizing large-scale fully programmable neural nets is currently being developed in our laboratory, and illustrates the potential role integrated photonics could play in the design and construction of a new generation of analog computers intended for use in neurocomputing and rapid simulation and study of nonlinear dynamical systems.

Neural Nets with Two-Dimensional Deployment of Neurons

Neural net architectures in which neurons are arranged in a two-dimensional (2-D) format to increase packing density and to facilitate handling 2-D formatted data have received early attention (see Farhat and Psaltis (1987) in list of further reading). These arrangements involve a 2-D N × N state "vector" or matrix s_{ij} representing the state of neurons, and a four-dimensional (4-D) connectivity "matrix" or tensor T_{ijkl} representing the weights of synapses between neurons. A scheme for partitioning the 4-D connectivity tensor into an N × N array of submatrices, each

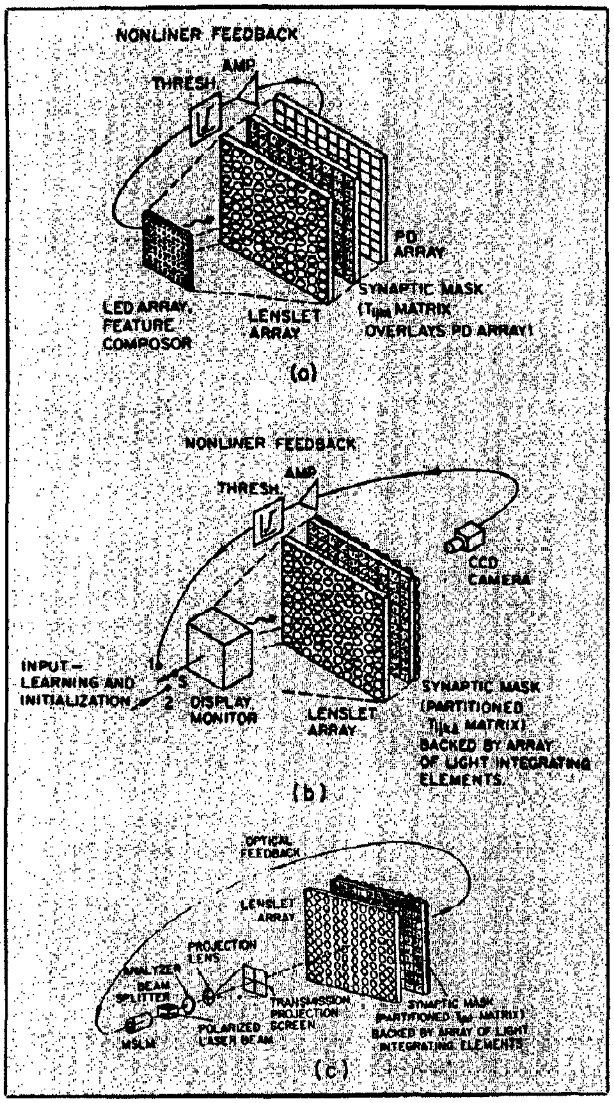

Fig. 6 Three optoelectronic network architectures in which the neurons are arranged in two-dimensional format employing: (a) parallel nonlinear electronic amplification and feedback, (b) serial nonlinear electronic amplification and feedback, (c) parallel nonlinear electron optical amplification and feedback.

of which has N × N elements, to enable storing it in a flat 2-D photomask or SLM for use in optoelectronic implementation has been developed (see Farhat and Psaltis 1987 in list of further reading). Several arrangements are possible using this partitioning scheme (see Fig. 6).

In Fig. 6(a), neuron states are represented with a 2-D LED array (or equivalently with a 2-D SLM). A two-dimensional lenslet array is used to spatially multiplex and project the state vector display onto each of the submatrices of the partitioned connectivity mask. The product of the state matrix with each of the weights stored in each submatrix is formed with the help of a spatially integrating square photodetector of suitable size positioned behind each submatrix. The (i-j)th photodetector output represents the activation potentials u_{ij} of the (i-j)th neurons. These activation potentials are nonlinearly amplified and fed back in parallel to drive the corresponding elements of the LED state array of those of the state SLM. In this fashion, weighted interconnections between all neurons are established by means of the lenslet array instead of the optical crossbar arrangement used to establish connectivity between neurons when they are deployed on a line.

Both plastic molded and glass micro-lenslet arrays can be fabricated today in 2-D formats. Glass micro-lenslet arrays with density of 9 to 25 lenslets/mm^2 can be made in large areas using basically photolithographic techniques. Resolution of up to ~50 ℓp/mm can also be achieved. Therefore, a micro lenslet array of (100×100)mm^2, for example, containing easily 10^5 lenslets could be used to form a net of 10^5 neurons provided that the required nonlinear light amplifiers (photodetector/thresholding amplifier/LED or SLM driver array) become available. This is another instance where integrated optoelectronics technology can play a central role. We have built a 8 × 8 neuron version of the arrangement in Fig. 6(a) employing a square LED array, a square plastic lenslet array, and a square PDA, each of which has 8 × 8 elements in which the state update was computed serially by a computer which sampled the activation potentials provided by the PDA and furnished the drive signals to the LED array. The connectivity weights in this arrangement were stored in a photographic mask which was formed with the help of the system itself in the following manner: Starting from a set of unipolar binary matrices b_{ij} to be stored in the net, the required 4-D connectivity tensor was obtained by computing the sum of the outer products of the bipolar binary versions $v_{ij} = 2b_{ij} - 1$. The resulting connectivity tensor was partitioned and unipolar binary quantized versions of its submatrices were displayed in order by the computer on the LED display and stored at their appropriate locations in a photographic plate placed in the image plane of the lenslet array by blocking all elements of the lenslet array except the one where a particular submatrix was to be stored. This process was automated with the aid of a computer controlled positioner scanning a pinhole mask in front of the lenslet array so that the photographic plate is exposed to each submatrix of the connectivity tensor displayed sequentially by the computer. The photographic plate was then developed and positioned back in place. Although time-consuming, this method of loading the connectivity matrix in the net has the advantage of compensating for all distortions and aberrations of the system.

The procedure for loading the memory in the system can be speeded up considerably by using an array of minute electronically controlled optical shutters (switches) to replace the function of the mechanically scanned pinhole. The shutter array is placed just in front or behind the lenslet array such that each element of the lenslet array has a corresponding shutter element in register with it. An electronically addressed ferroelectric liquid crystal spatial light modulator (FeLCSLM) (see Spatial Light Modulators and Applications in list of further reading) is a suitable candidate for this task because of its fast switching speed (a few microseconds). Development of FeLCSLMs is being pursued worldwide because of their speed, high contrast, and bistability which enables nonvolatile switching of pixel transmission between two states. These features make FeLCSLMs also attractive for use as programmable connectivity masks in learning networks such as the Boltzmann machine in place of the MOSLM presently in use.

Because the connectivity matrix was unipolar, an adaptive threshold equal to the mean or energy of the iterated state vector was found to be required in computing the update state to make the network function as an associative memory that performed in accordance with theoretical predictions of storage capacity and for successful associative search when sketchy (noisy and/or partial) inputs are presented. Recent evidence in our work is showing that ligistic neurons, mentioned in a footnote earlier, allow using unipolar connectivity weights in a network without having to resort to adaptive thresholding. This behavior may be caused by the possibility that logistic neurons, with their "humped" nonsigmoidal response, combine at once features of excitatory and inhibitory neurons which, from all presently available evidence, is biologically not plausible. Biological plausibility, it can be argued, is desirable for guiding hardware implementations of neural nets but is not absolutely necessary as long as departures from it facilitate and simplify implementations without sacrificing function and flexibility.

Several variations of the above basic 2-D architecture were studied. One, shown in Fig. 6(b) employs an array of light integrating elements (lenslet array plus diffusers, for example) and a CCD camera plus serial nonlinear amplification and driving to display the updated state matrix on a display monitor. In Fig. 6(c) a microchannel spatial light modulator (MCSLM) is employed as an electron-optical array of thresholding amplifiers and to simultaneously display the updated state vector in coherent laser light as input to the system. The spatial coherence of the state vector display in this case also enables replacing the lenslet array with a fine 2-D grating to spatially multiplex the displayed image onto the connectivity photomask. Our studies show that the 2-D architectures described are well suited for implementing large networks with semi-global or local rather than global interconnects between neurons, with each neuron capable of communicating with up to few thousand neurons in its vicinity depending on lenslet resolution and geometry. Adaptive learning in these architectures is also possible provided a suitable erasable storage medium is found to replace the photographic mask. For example in yet another conceivable variant of the above architectures, the lenslet array can be used to spatially demultiplex the connectivity submatrices presented in a suitable Z-D erasable display, i.e. project them in perfect register, onto a single SLM device containing the state vector data. This enables forming the activation potential array u_{ij} directly and facilitates carrying out the required neron response operations (nonlinear gain) optically and in parallel through appropriate choice of the state vector SLM and the architecture. Variations employing internal feedback, as in 1-D neural nets, can also be conceived.

Discussion

Optoelectronics (or photonics) offers clear advantages for the design and construction of a new generation of analog computers (neurocomputers) capable of performing computational tasks collectively and dynamically at very high speed and as such, are suited for use in the solution of complex problems encountered in cognition, optimization, and control that have defied efficient handling with traditional digital computation even when very powerful digital computers are used. The architectures and proof of concept prototypes described are aimed at demonstrating that the optoelectronic approach can combine the best attributes of optics and electronics together with programmable non-volatile spatial light modulators and displays to form versatile neural nets with important capabilities that include associative storage and recall, self organization and adaptive learning (self-programming), and fast solution of optimization problems. Large-scale versions of these neurocomputers are needed for tackling real world problems. Ultimately these can be realized using integrated optoelectronic (integrated photonic) technology rather than the hybrid optoelectronic approach presented here. Thus, new impetus is added for the development of integrated optoelectronics besides that coming from the needs of high speed optical communication. One can expect variations of integrated optoelectronic repeater chips utilizing GaAs on silicon technology being developed with optical communication in mind (see J. Shibata and T. Kajiwara in list of further reading). These, when fabricated in dense array form, will find widespread use in the construction of large-scale analog neurocomputers. This class of neurocomputers will probably also find use in the study and fast simulation of nonlinear dynamical systems and chaos and its role in a variety of systems.

Biological neural nets were evolved in nature for one ultimate purpose: that of maintaining and enhancing survivability of the organism they reside in. Embedding artificial neural nets in man-made systems, and in particular autonomous systems, can serve to enhance their survivability and therefore reliability. Survivability is also a central issue in a variety of systems with complex behavior encountered in biology, economics, social studies, and military science. One can therefore expect neuromorphic processing and neurocomputers to play an important role in the modeling and study of such complex systems especially if integrated optoelectronic techniques can be made to extend the flexibility and speed demonstrated in the prototype nets described to large scale networks. One should also expect that software development for emulating neural functions on serial and parallel digital machines will not continue to be confined, as at present, to the realm of straightforward simulation, but spurred by the mounting interest in neural processing, will move into the algorithmic domain where fast efficient algoriths are likely to be developed, especially for parallel machines, becoming to neural processing what the FFT (fast Fourier transform) was to the discrete Fourier transform. Thus we expect that advances in neuromorphic analog and digital signal processing will proceed in parallel and that applications would draw on both equally.

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Buckley Running as Write-In Candidate

Merrill W. Buckley, Jr. is running as a write-in candidate for President Elect of the IEEE. Mr. Buckley has much experience in defense and aerospace and has held many important positions in IEEE. His ideas for the future are interesting and should be explored and compared with the other candidates. The last successful write-in candidate was Leo Young.