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REPORT ON THE WORKSHOP ON OPTICAL NEURAL NETWORKS

Final Report for AFOSR 89-NE-355, Dr. Alan Craig
and for ONR N00014-90-J-1990, Dr. Wm. Miceli

Prepared by

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Boulder, Co 80309-0425

September 28, 1990

Thirty-nine researchers attended the Workshop on Optical Neural Networks held in Jackson, Wyoming this past February 7-10, 1990. The Workshop, sponsored by the Air Force Office of Scientific Research and the Office of Naval Research, was organized by Lee Giles (NEC Research Institute), Demetri Psaltis (California Institute of Technology), and Kelvin Wagner (Optoelectronic Computing Systems Center, University of Colorado at Boulder). Its purpose was to critically examine the status of optical neural network research and evaluate its present and future role, particularly as an implementation technology for neural network models of computation.

The workshop participants included researchers in optical neural networks as well as experts in related fields such as active optical devices, VLSI implementation of neural networks, and neural network architectures, algorithms, and theory. The format of the workshop included both presentation and discussion sessions. Each participant had prepared a 15 minute presentation. These presentations served as the context for the discussion sessions. A brief summary of some of these presentations and discussions is presented below.

1 Introduction

Neural networks typically consist of weighted global interconnections between arrays of simple nonlinear units. Their output is usually a soft threshold version of the weighted and summed inputs from other neurons. Learning dynamics are used to evolve the interconnection weight matrices as a succession of small perturbations, usually implemented as sums of outer products. These are the essential features that must be incorporated into any hardware implementation of a neural network.

Optical techniques are being considered for the implementation of neural network models of computation because of several unique properties of optical systems. These include the three-dimensional topology of optical systems, and the ability of optical beams to cross through one another in free space, allowing the compact implementation of global interconnect networks. In addition, the continuous analog nature of optical systems can be combined

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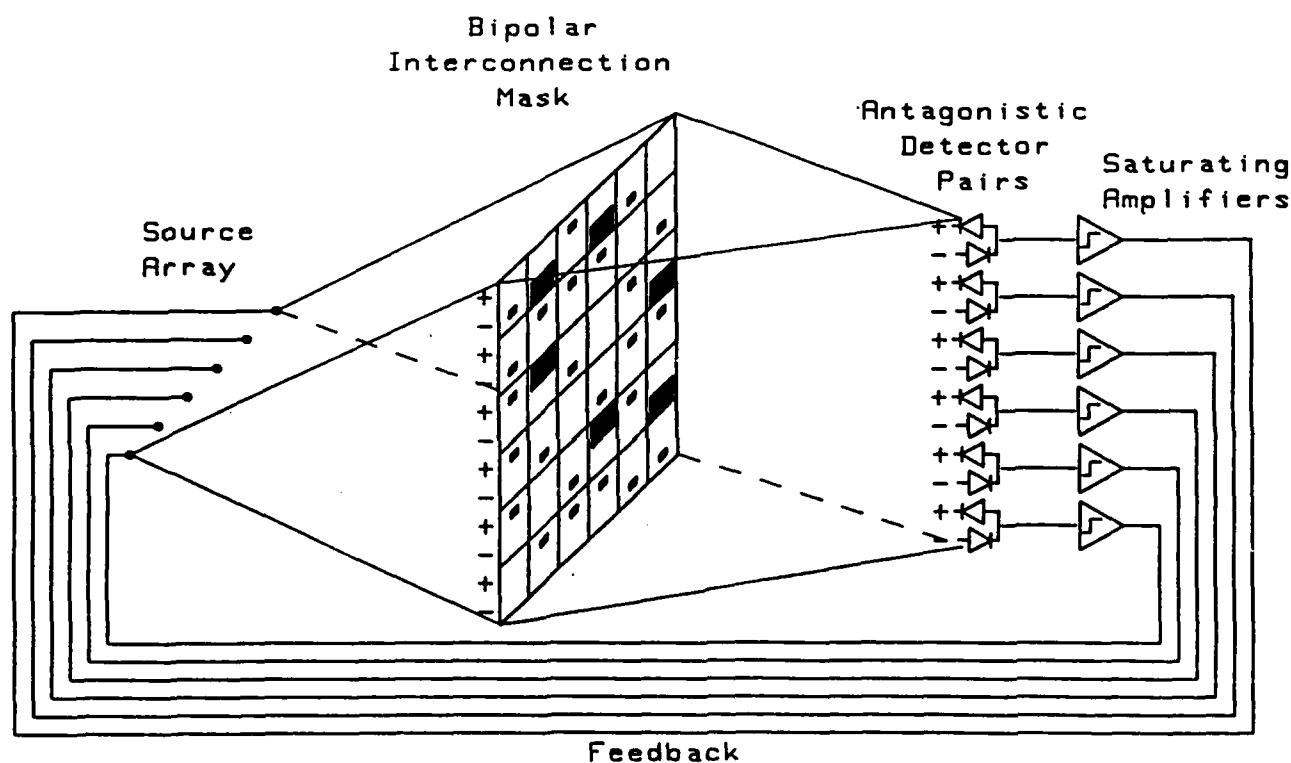


Figure 1: a: The spatial light modulator based approach to optical neural networks.

VOLUME HOLOGRAPHIC ASSOCIATION

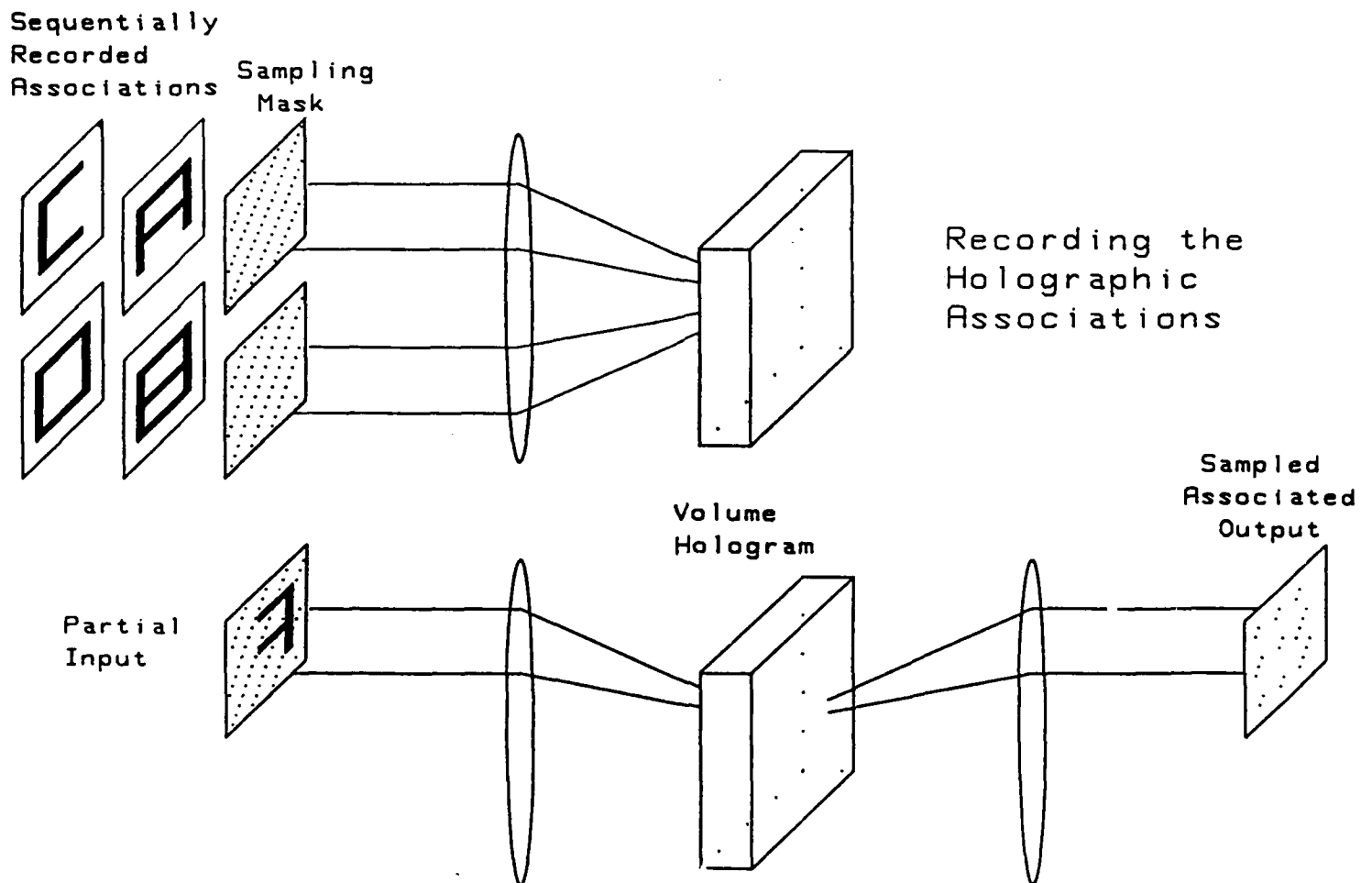


Figure 2: b: The holographic approach to optical neural networks using volume holograms.

with nonlinear optical devices to implement nonlinear dynamical systems which are a good match to neurodynamical models of computation and learning.

Optical approaches to the implementation of neural networks are usually based on one of two distinct techniques for implementing the weighted interconnections required by the neural models. The first approach, shown in Figure 1, uses the variable transmittance of a pixel in a two-dimensional spatial light modulator (SLM) to represent the weight of an interconnection. The second approach, shown in Figure 2 uses the programmable diffraction efficiency of a holographic grating to represent the weight of an interconnection. Both techniques rely on spatial broadcasting and spatial collection of the weighted outputs to complete the required matrix vector multiplication. A potential advantage of the holographic technique that was emphasized by several conference participants is the ability to utilize volume holograms to store the interconnection gratings in three dimensions, as shown in Figure 2. This allows a tremendous density of weighted interconnections to be realized, and the use of dynamic materials (such as photorefractive crystals) allows the implementation of real-time learning in the optical domain. This is based on an extension of the holographic metaphor for associative memory proposed by Van Heerden and Gabor more than 20 years ago. Three key developments that distinguish modern optical neural network research from earlier pioneering work on holographic association are the incorporation of dynamic learning algorithms, the central role played by the neural nonlinearity, and the utilization of fractal topologies in order to fully realize the global interconnection capabilities of volume holograms.

2 Learning Systems

The most distinctive feature of neural network models of computation is the ability to learn from experience. This is accomplished by adaptively modifying the strength of the interconnections between the neurons. In optical systems, these weights are usually represented as the diffraction efficiency of holographic gratings or as the transmittance of pixels in a spatial light modulator. Neural learning algorithms give rules for the adaptive modification of these interconnections or weights, which are almost always based on iterative outer product perturbations of the weight matrix. This can be mapped into optics as either associative holographic recording or as the product of crossed one-dimensional light modulators addressing a two-dimensional optically addressed spatial light modulators.

2.1 Photorefractive perceptrons

Several successful optical learning demonstrations using photorefractive crystals were presented at this Workshop. David Brady (University of Illinois, Urbana-Champaign) discussed the limitations of controlling dynamic volume holograms, since the N^3 internal degrees of freedom must be accessed through the faces, which permit the addressing of only N^2 independent control parameters. In neural learning applications, outer products are formed with holographic interference between patterns sampled on appropriate fractal grids that modify all N^3 internal degrees of freedom, but not independently. A sequence of exposures must be used to write interconnection matrices into a volume hologram, and exposure scheduling needs to be employed to maximize the diffraction efficiency, which is decreased due to the

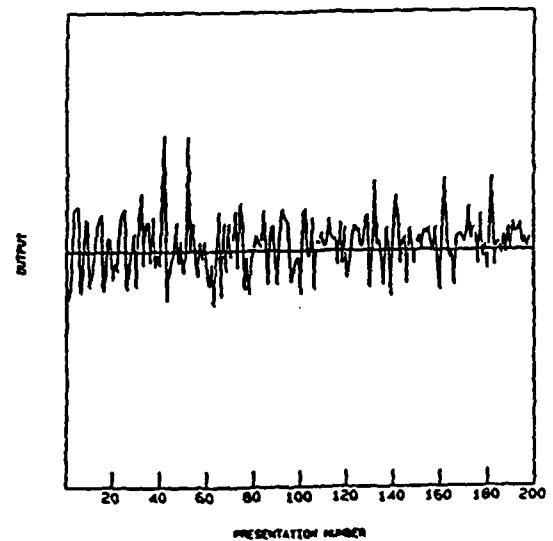
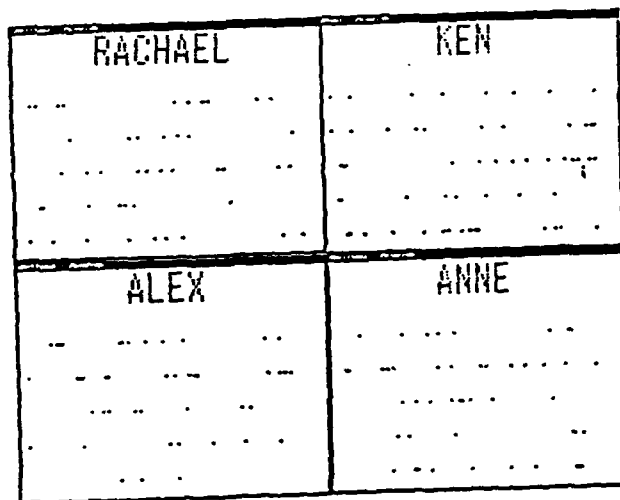
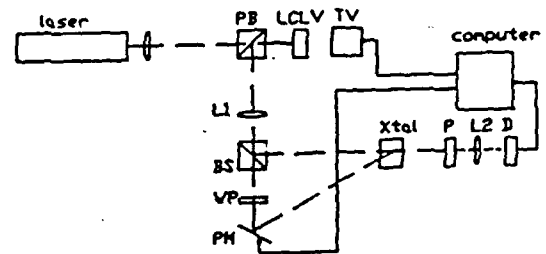
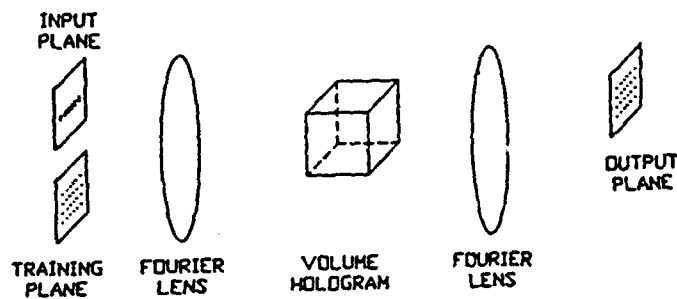


Figure 3: Schematic illustration of volume hologram association, and a simple learning system. Input output pairs on the fractal grids and the experimental learning curve. Figure credit: David Brady, Photorefractive volume holography in artificial neural networks, PhD Thesis, Caltech 1990.

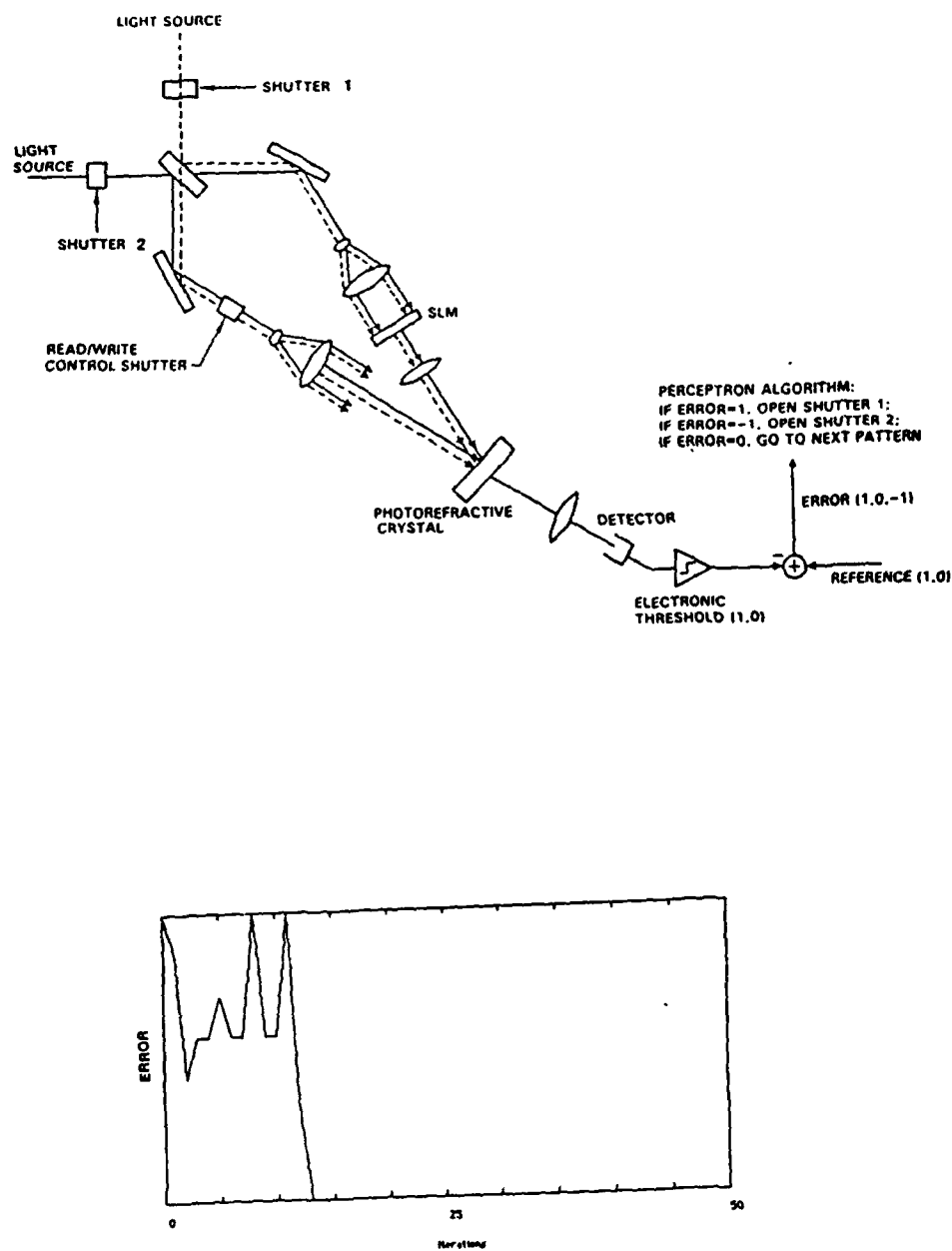
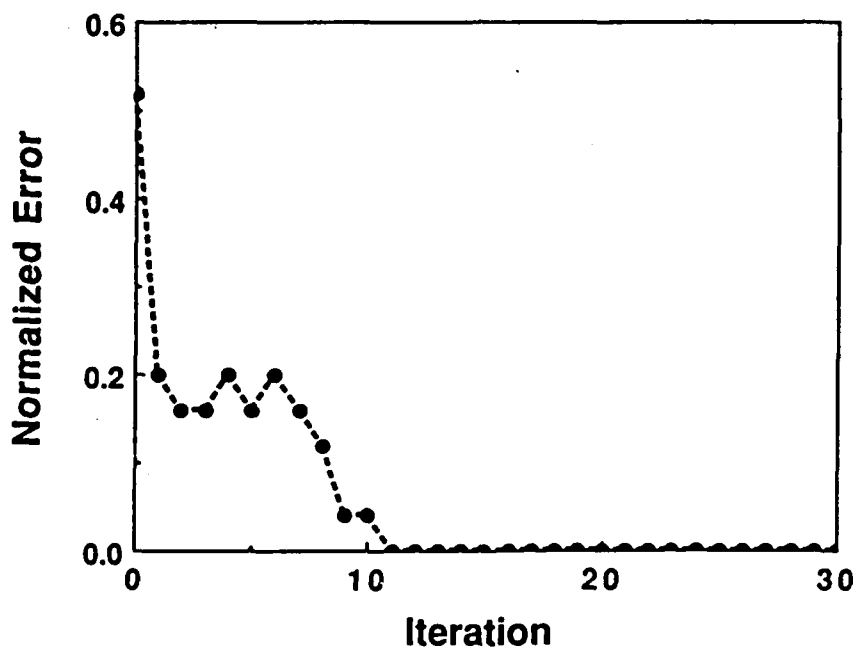
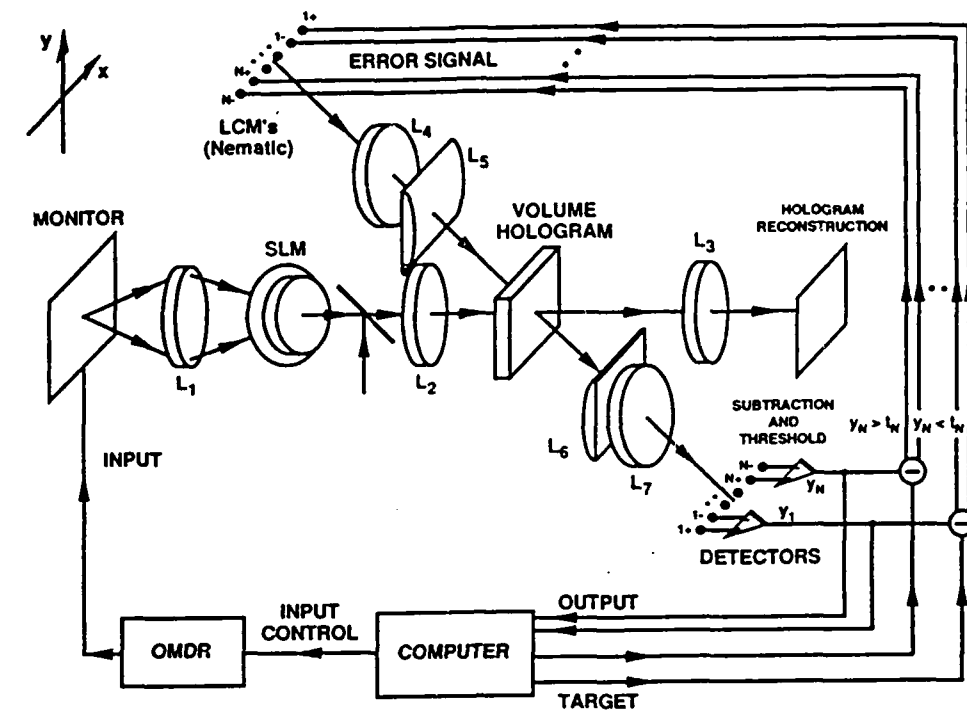


Figure 4: Schematic diagram of the perceptron optical pattern classifier using a photorefractive crystal. Figure Credit: John Hong, Scott Campbell, and Pochi Yeh, Optical pattern classifier with perceptron learning, *Applied Optics*, vol 29(20), p. 3019 (1990).



Experimental learning curves for five training patterns (A, B, C, D, and E).

Figure 5: Schematic of the holographic learning machine for multcategory classification. Figure Credit: Eung Gi Paek, et al., Optics Letters, Vol. 14 (23), p. 1304, 1989.

effect that subsequent exposures partially erase earlier ones. He also showed the results of a photorefractive perceptron which associated 500 input random patterns with 500 pixel names, shown in Figure 3, where the weight decrements required by the learning algorithm were implemented using incoherent erasure.

John Hong (Rockwell Science Center, Thousand Oaks, CA) demonstrated the successful operation of a photoreceptive perceptron. His system, shown in Figure 4, uses coherent erasure to decrease the adaptive weights, where a π phase shifted grating is written on top of an existing grating using a double mach-zehnder interferometer, thereby partially canceling the initial grating.

Eung Gi Paek (Bellcore, New Jersey) also presented a perceptron learning system that uses a photorefractive crystal as the adaptive weights. The system, shown schematically in Figure 5, had 250,000 input neurons and 10 bipolar outputs. His research demonstrated that a multiple output perceptron could be implemented by multiplexing gratings in a volume medium without unwanted crosstalk. Both Paek's and Hong's systems exhibited anomalous unlearning due to incoherent erasure in the crystals after the desired pattern associations had been learned and were simply being read out. This may be a severe problem for the optical implementation of adaptive systems using photorefractive holograms unless a compensating learning algorithm, or nondestructive readout technique is utilized.

2.2 SLM based learning systems

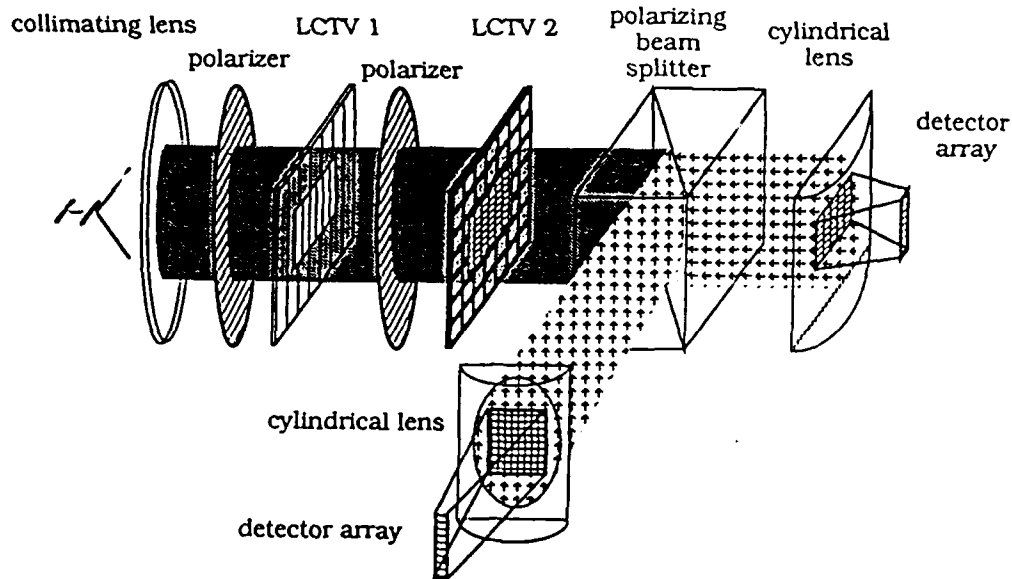
Successful learning was also obtained in systems employing SLMs as the adaptive interconnections. Kristina Johnson (OCS Center, CU-Boulder) presented results of single-layer and multi-layer learning experiments in a polarization based liquid crystal optical connectionist machine. (See Figure 6.) This optical connectionist machine has performed back propagation learning that successfully predict solar flare activity given 32 coded input and 3 labeled output neurons when trained on 200 patterns of sunspot data. The learning dynamics, which were controlled by the feedback computer, successfully compensated for several varieties of noise due to imperfections in the optics.

Nabil Farhat (University of Pennsylvania) presented work on Boltzmann machine learning using binary spatial light modulators. He showed how a multilayered network can be implemented in a single layer of hardware by partitioning the weight matrix into a number of blocks representing the interconnections between different layers as shown in Figure 7. Dr. Farhat and Dr. Anderson also discussed phase space engineering techniques which describes their approach to designing an optical neural network. This entails the design of the path of a complex system through its state space and represents a computation as the state space evolution of the system.

3 Optical Synapse Technology

The successful realization of optical neural networks is dependent upon the availability of components that can act as neurons and synapses. The optical synapses must weight the interconnections between the neurons. The ability to be dynamically modify these synapses is required in order to implement adaptive learning algorithms.

Optoelectronic Computing Systems Center



Nematic Liquid Crystal Optical Connectionist Machine

University of Colorado

OCM and Simulator Learning

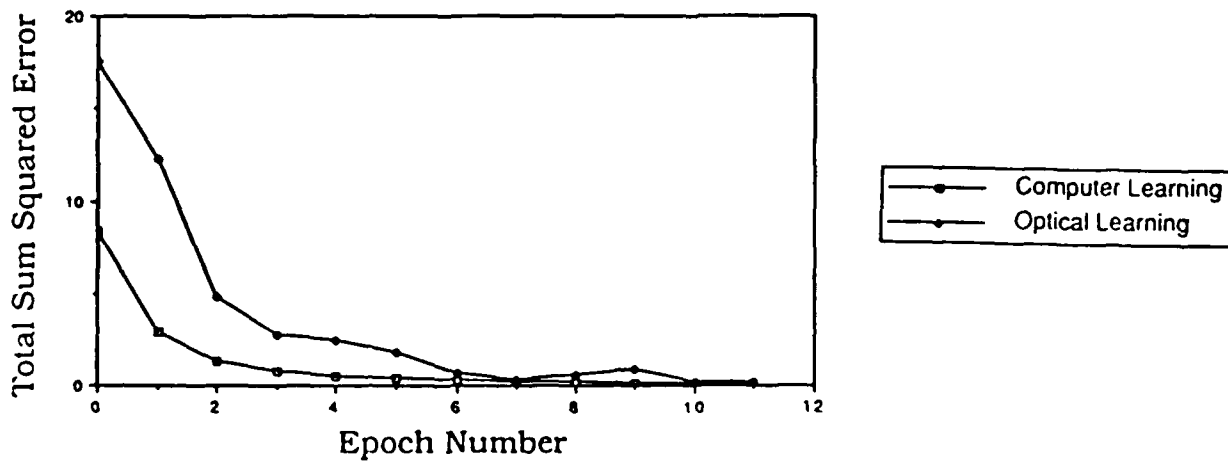


Figure 6: The polarization-based optical connectionist machine at the University of Colorado is pictured here. Figure credit: Kristina Johnson

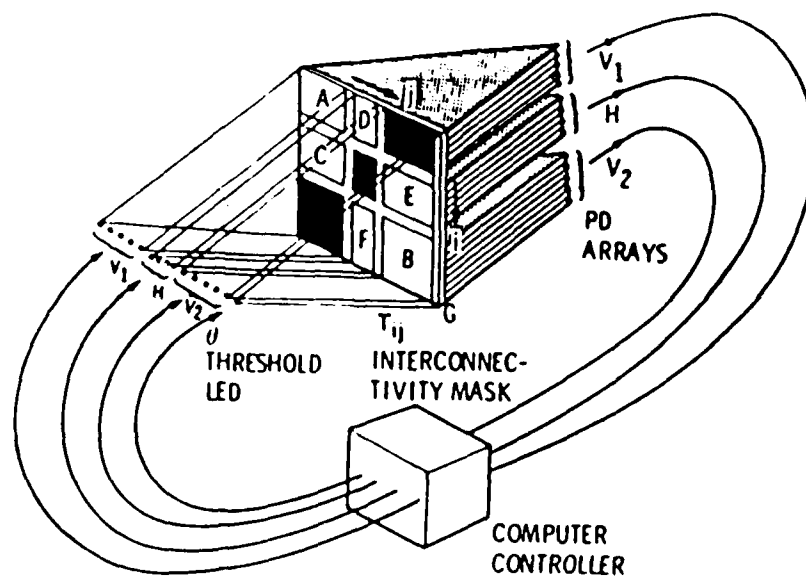


Figure 7: Optoelectronic analog of self-organizing neural net partitioned into three layers capable of stochastic self-programming and learning. Figure credit: Nabil Farhat, Applied Optics, Vol.26 23), p. 5097, 1987.

3.1 Dynamic volume holograms

Holographic interconnections using dynamic volume holograms were discussed by several participants. A major difficulty with these materials is the incoherent erasure that occurs while the holograms are being read out, which results in the unlearning phenomena observed by Paek and Hong. This incoherent erasure problem in photorefractives can be alleviated by inducing a read-write asymmetry.

Henri Rajenbach (Thomson-CSF, France) presented preliminary results of hole fixing in cooled BSO that resulted in the ability to continuously read out images for several hours without erasure. This is possible because a photogenerated hologram written by the electrons is compensated by the holes, and at low temperatures the hole mobility is much lower than the electron mobility, so that a hologram written as spatial modulations of the hole density remains frozen into the crystal.

Fai Mok (Northrup Corp. Research and Technology Center, Palos Verdes, CA) presented results of multiple image storage in $\text{LiNbO}_3\text{:Fe}$ that used thermal fixing and exposure scheduling to compensate for erasure during writing, and also eliminates erasure during read-out. He has successfully stored and retrieved over 500 high quality images of over 60,000 pixels each, with greater than .01% diffraction efficiency each. The holograms were recorded with a 300:1 beam ratio at an angular separation of .02 degrees, and exposure scheduling was used in order to obtain a diffraction efficiency uniformity of about 25%.

Kelvin Wagner (University of Colorado, Boulder CO) showed samples of organic volume holograms based on photochemical dyes suspended in a polymer matrix that may find applications in optical neural networks. These materials exhibit high diffraction efficiency and show both permanent and dynamic holographic recording capabilities that may be useful for avoiding unlearning associated with erasure. The very low cost and large size may give them a competitive economic advantage over the more costly and fragile photorefractive crystals commonly employed.

Dana Anderson (OCS Center, CU-Boulder) showed winner-take-all behavior in sequential recall dynamics in a multi-crystal photorefractive resonator, shown in Figure 8. These type of winner-take-all dynamics give the optical system an important decision making capability that forms the basis of a wide variety of unsupervised learning algorithms. Dr. Anderson believes that the computation dynamics inherent to the photorefractive circuits may be applied as a very general technique for obtaining almost any dynamics provided one has a sufficient number of modes and sufficient control over the mode interactions. Furthermore, this class of optical system is one of the few physical systems that can embed continuous distributions of neural activity processing in continuous time.

3.2 Fixed planar holograms

Art Gmitro (University of Arizona) and Henry J. White (British Aerospace) both presented analysis of the limitations of space variant weighted interconnections using E-Beam written computer-generated holograms for interconnecting two-dimensional neuron arrays displayed on liquid crystal light valves. They both concluded that up to about 64×64 neuron arrays could be globally interconnected in order to implement a nonadaptive optical neural network using this technique. However, larger networks would be beyond the technological capabil-

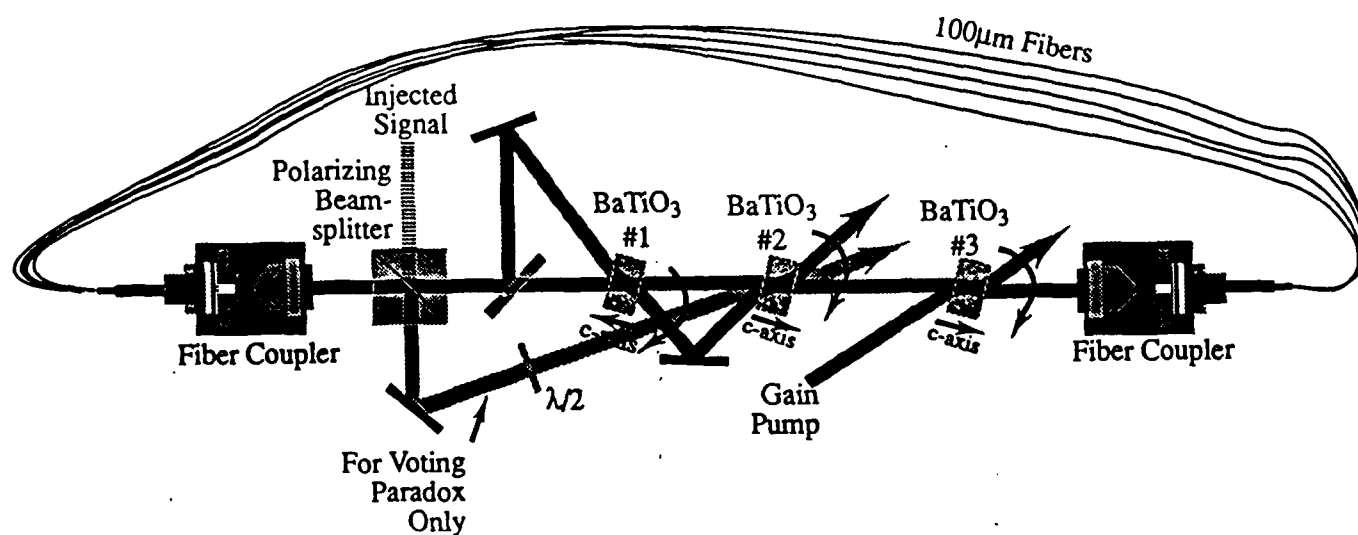


Figure 8: Optical resonator implementing a winner-take-all dynamics. Crystal 1 is in the Fourier plane of the vertically multiplexed fiber array while crystal 2 is in the image plane, crystal 3 just provides gain. Figure credit: Dana Anderson

ities of this technology. This is because the size and resolution requirements of a space variant interconnection hologram for an $N \times N$ neuron array grow as $KN^2 \times KN^2$, where K is an oversampling factor, typically greater than 10, and the overall space-bandwidth product is constrained to be less than $10^5 \times 10^5$ by the e-beam machines. In addition, due to various crosstalk and sidelobe terms, the accuracy of these weighted interconnects might be too low for some applications (such as neural optimizers) but it may be sufficient for optical associative memory.

Alan Yamamura (California Institute of Technology) presented new results of writing computer generated holograms on Sony's sampled-format optical disks. Holographically reconstructed weight matrices were written onto optically programmed VLSI neural chips to control the electronic interconnect topology from the optical domain. This allows rapid reprogrammability of the interconnections in order to implement multilayer networks.

4 Optical Neuron Technology

Simple optical neurons need to sum a huge number of weighted inputs and produce a threshold output. The goals, stated in an introduction by Demetri Psaltis (California Institute of Technology, Pasadena), are to produce devices with more than 10,000 neurons with a response time in the microsecond range, with gain much greater than 10, and power dissipation well below a milliwatt. Although such a device capability is not yet available, several technologies appear to be approaching this goal.

4.1 FLC modulators

Ferroelectric liquid crystals are a promising candidate for implementing large arrays of low power neurons. Garret Moddel (OCS Center, CU-Boulder) illustrated the capabilities of an amorphous silicon ferroelectric liquid crystal (FLC) optically-addressed spatial light modulator (OASLM) using smectic C* and smectic A* materials. The smectic A* device achieves as low as a 4 microsecond response time for a high resolution SLM (~ 70 lp/mm) with significantly more than 1000×1000 pixels, requiring significantly below .1pJ/pixel switching energy. These capabilities make this an almost ideal device for implementing optical neurons. Even further improvements can be made by including a third terminal, which his group recently demonstrated, allowing them to implement a variable threshold device.

Tim Drabik (Georgia Institute of Technology, Atlanta) presented recent results on a silicon VLSI chip coated with FLC that incorporated a 16×8 array of photodetectors where each detector drove a modulating pad containing the FLC and acted as an optically-addressed SLM. This device may have application as an optical neuron array or as an early vision optical preprocessor. He also showed results of a high frame rate electrically addressed 64×64 SLM that might be used for entering data into an optical neural network.

4.2 GaAs modulators, LEDS and laser diodes

Another promising approach is to use optoelectronic GaAs modulators and sources such as LEDs and laser diodes driven by electronic photo-detectors. Several variants were proposed

for optical neurons, and their properties were compared and contrasted.

Tony Lentine (AT&T Bell Labs, Naperville, IL) showed results of a 1.5pJ switching energy symmetric self- electro-optic-effect device (S-SEED). Arrays of those devices can implement loser-take-all dynamics by electrically interconnecting them in series. Although this is the opposite of the winner-take-all dynamics required in many neural models, it can be modified by following with a separate optical inversion stage.

Jaspri Singh (university of Michigan, Ann Arbor) suggested that SEEDs were not suited to neural networks, but could be modified by placing the seed inside of a heterojunction bipolar transistor, rather than inside a PIN diode as conventionally done. Not only could this allow the utilization of the HBT-SEED as a neuron, but it might also be used as an adaptive synapse mask.

J. Cheng (University of New Mexico, Albuquerque) presented arguments in favor of the use of micropower laser diodes and vertical cavity surface emitting lasers as the sources for optical neurons. This is motivated by the excellent optical properties and diffraction limited performance of these sources, as well as by the high differential quantum efficiency that can be achieved. He suggested that a photodarlington giving each microlaser could provide the necessary optical neuron functions.

Demetri Psaltis showed results of a 10x10 array of phototransistor darlington amplifier LED neuron array fabricated in GaAs. LEDs were chosen instead of more efficient diodes because they have no current threshold and the power dissipation of a very large array of optical neurons can be minimized. His arguments go as follows, the total output power of an array of N laser diodes is given by

$$P_{optical}^{LD} = N\eta(i - i_{th})h\nu/q$$

where $\eta \approx .3 - .7$ is the external differential quantum efficiency and includes the resonator and loss effects, i is the input current, while $i_{th} \approx 1\text{mA}$ is the threshold current for a low threshold laser. Similarly the total output power of an array of N' LEDs is given by

$$P_{optical}^{LED} = N'\eta'i'h\nu/q$$

where $\eta' \approx .01$ is the efficiency for an LED, and i' is the drive current. For both the laser and LED the dissipation is given by $P_{dis} = iv$ and the drive voltage for both must be above the bandgap. For a fixed power requirement as the number of neurons is increased, the total efficiency of the lasers drop since they are operated closer to threshold, while for the LEDs the efficiency remains constant. Therefore, for more than about 1000 neurons emitting a few mW, the LEDs are preferable. However, if Watts of optical power is required, then laser diodes would have significantly better overall efficiency.

5 Implications of Neural Network Theory

Neural network theory has several implications on the requirements and limitations of optical neural networks. These issues were discussed at length during the Workshop. Two specific consequences are mentioned here.

5.1 dynamic range requirements on synapses

Santosh Venkatesh (University of Pennsylvania) presented results on the required dynamic range of synapses and showed that with binary synapses storage capacity is only reduced by a factor of two from real synapses. He presented a simple directed drift learning algorithm for these binary synapses and concluded that low dynamic range optical synapses may be adequate for many applications. This, however, did not alleviate the dynamic range requirements of the neurons, nor did it address the issue of contrast ratio or noise.

5.2 Issues in training and generalization

Eric Baum (NEC Research Institute, Princeton, NJ) discussed the limitations inherent to learning from examples and concluded that the huge number of interconnects available in optical systems may require a huge number of training exemplars in order to achieve valid generalization. One suggestion to alleviate the unfavorable scaling properties of huge networks was to grow or prune the networks to fit the task. He suggested that the superabundance of resources in optics may allow fast learning, followed by pruning, to achieve a minimal optical network quickly and obtain good generalization.

John Denker (AT&T Bell Laboratories, Holmdel NJ) discussed the difference between capacity and generalization in a neural network, and illustrated the importance of massively exceeding capacity to insure valid generalization. Since the type of real world pattern recognition problems likely to be processed on an optical neural network are somehow structured in a very high dimensional space and manifestly not random, the capacity arguments invoked for randomly selected patterns should be applied cautiously.

6 Some Conclusions

The issues brought to light are challenging ones. In face of rapid developments in electronic technologies, are optical neural networks truly viable? The discussions were lively, and opinions were frankly expressed by the participants, although universal agreement was not achieved.

6.1 Comparison with VLSI neural networks

A major topic of discussion was the viability of optical neural networks in light of the incredible advances foreseen in the electronic implementation of neural networks. Larry Jackel (AT&T Bell Labs, New Jersey) and Josh Allspector (Bellcore, New Jersey) illustrated the great potential of the VLSI approach to neural networks with numerous examples of fabricated chips. However, VLSI neural networks are limited to two dimensions while optics can make use of the three-dimensional storage capacity of volume holograms which allows the compact realization of huge networks with N310,000 neurons, well beyond the projected capabilities of VLSI. The trainability of such networks and the search for problems that inherently require these large networks are still open questions.

6.2 Fault tolerance

Several researchers emphasized that the optical implementations of adaptive networks are capable of learning out some of the imperfections inherent to optical systems. Because of this these systems may stand a better chance for success than other optical computing paradigms since they are inherently more fault tolerant and robust.

6.3 Biology and neural network theory

The importance of biological principles was emphasized by several researchers since the brain provides an existence proof of the utility of the neural paradigm. There is, however, currently a mismatch between theoretical models and optical implementation because many of the models are derived directly from biological principles or intended for VLSI Implementation rather than optical, and a closer coupling between optics and neural network theory was suggested.

6.4 Applications of optical neural networks

Many discussions centered around applications appropriate for optical neural nets. Image recognition, an inherently two-dimensional problem, seem to be a natural match for optics, especially if the shift invariant properties of Fourier optical systems can be combined with some recent neural models that require correlation. Problems such as AI data base searches may also be able to take advantage of the huge storage capacity and dimensionality of optical systems. Naturally dynamical problems such as speech and radar may find ideal matches in nonlinear dynamical optical systems.

A final conclusion of the workshop was that optical neural networks need to be applied to a large-scale application problem well beyond the capabilities of electronics in order to demonstrate the viability of this nonconventional approach to computation.

7 Future Plans

The workshop was quite successful as a vehicle leading to important discussions, critical self evaluation, and directing future research in the most advantageous and necessary directions. A follow on workshop may be held in early 1992.

8 Acknowledgements

This report was prepared with the assistance of Demetri Psaltis, California Institute of Technology, Lee Giles, NEC Research Institute, and Marilee Dunn, of the University of Colorado. The assistance of Chris Slinger, Dana Anderson, and Kristina Johnson in summarizing the conference is gratefully acknowledged. Portions of this report appeared in the Laser Focus Optical Computing Newsletter published August 1990, p. 127-130, and edited by Marilee Dunn.

WORKSHOP ON OPTICAL NEURAL NETWORKS

February 7-10, Jackson WY

39 attendees from the US, UK, France, and West Germany

3 $\frac{1}{2}$ day workshop emphasizing discussion

Presentation Sessions

Complexity and Limitations of Neural Networks

Optical Neural Network Architectures

Optical Learning

Learning Theory

Optoelectronic Neural Networks

Holographic Optical Neural Networks

Devices for Optical Neurons

Devices for Optical Synapses

VLSI Networks Compared to Optics

Optical Interconnects

Applications of Optical Neural Networks

Discussion Sessions

Accuracy, Scalability, and Noise

Off-line vs Real-time learning

Learning

2D vs 3D implementations

Required Technological Advances

LEDs vs Lasers vs Modulators as Optical Neurons

VLSI vs Optical vs Hybrid Implementations of Neural Networks

Applications of Optical Neural Networks

Advantages and Limitations of Optical Neural Networks

SCHEDULE - Jackson workshop on Optical Neural Networks, Feb 7-10

Wednesday, February 7 Evening session

6:00-7:00	Dinner
7:30-7:45	Organization and Welcome D. Psaltis
7:45-8:45	Complexity and Limitations of NN - John Denker
7:45-8:05	S. Venkatesh
8:05-8:25	E. Baum
8:25-9:00	Discussion of accuracy, scalability, and noise
9:00-9:40	Optical Neural Network Architectures - Dana Anderson
9:00-9:20	N. Farhat
9:20-9:40	K. Wagner
9:40-10:00	Discussion of why optics
10:00 -	Snacks

Thursday, February 8

Morning session

7:00-8:00	Buffet breakfast
8:00-9:00	Optical learning - Kelvin Wagner
8:00-8:20	E. Paek
8:20-8:40	K. Johnson
8:40-9:00	D. Brady
9:00-9:20	J. Hong
9:00-9:45	Discussion of off-line vs real-time vs computerized learning
9:45-10:15	Coffee Break
10:15-11:30	Learning Theory - Larry Jackel
10:15-10:35	J. Denker
10:35-10:55	L. Giles
10:55-11:30	Discussion of learning
11:30	Lunch

Evening session

6:00-7:00	Dinner
7:00-7:40	Optoelectronic neural networks - Nabil Farhat
7:00-7:20	G. Haussler
7:20-7:40	A. Yamamura
7:40-9:15	Holographic Optical neural nets - Demetri Psaltis
7:40-8:00	D. Anderson
8:00-8:15	E. Hartman
8:15-8:30	Break
8:30-8:45	H.J. White
8:45-9:00	A. Gmitro
9:00-9:15	H. Rajenbach
9:30-10:00	Discussion of 2D vs 3D implementations
10:00-	Snacks

Friday, February 9

7:00-8:00

8:00-9:30

8:00-8:15

8:15-8:30

8:30-8:45

8:45-9:00

9:00-9:15

9:15-9:30

9:30-10:00

10:00-10:45

10:00-10:15

10:15-10:30

10:30-10:45

10:45-11:30

11:30

Morning session

Buffet breakfast

Devices for optical neurons - Kristina Johnson

S. Esener

D. Psaltis

J. Cheng

J. Singh

T. Lentine

T. Drabik

Coffee Break

Devices for adaptive optical synapses - Josh Allspector

G. Modell

C. Warde

F. Mok

Discussion of required technological advances

Lunch

Evening session

Dinner at the Cadillac Grill

5:30-7:30

7:30-8:30

7:30-7:50

7:50-8:10

8:10-8:30

8:30-9:30

8:30-8:50

8:50-9:10

9:10-9:30

9:30-10:00

10:00-

VLSI neural networks compared to optics - Sing Lee

L. Jackel

J. Allspector

K. Kornfield

Optical interconnects - Sadik Esener

M. Prise

D. Chiarulli

S. Levitan

Discussion of VLSI vs digital vs optics vs hybrid implementations

Snacks

Saturday, February 10

7:00-8:00

8:00-9:00

8:00-8:20

8:20-8:40

8:40-9:00

9:00-10:00

9:00-9:15

9:15-9:30

9:30-9:45

9:45-10:00

10:00-10:30

10:30-11:00

11:00-11:30

11:30

Morning session

Buffet breakfast

Optical interconnects 2 - Bill Miceli

S. Lee

P. Lalanne

C. Slinger

Applications of ONN - Lee Giles

W. Miceli

J. Yu

A. Craig

Coffee Break

Discussion of appropriate algorithms and applications for ONN**Discussion of advantages and limitations of ONN****Summary and Conclusions**

Lunch and Adjourn

Successful Demonstrations of Optical Learning

E. Paek, Bellcore

250,000 inputs, 10 outputs, dual rail bipolar

Perceptron learning in photorefractive using electronic feedback

Problems with erasure in photorefractives

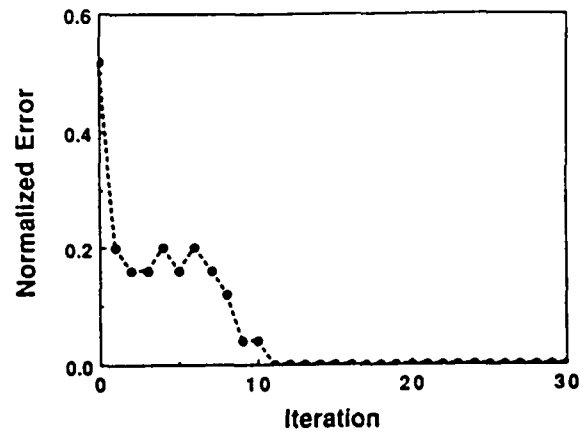
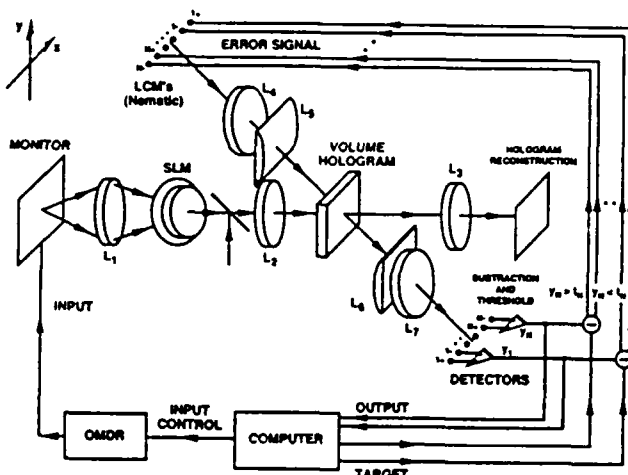


Fig. 3. Experimental learning curves for five training patterns (A, B, C, D, and E).

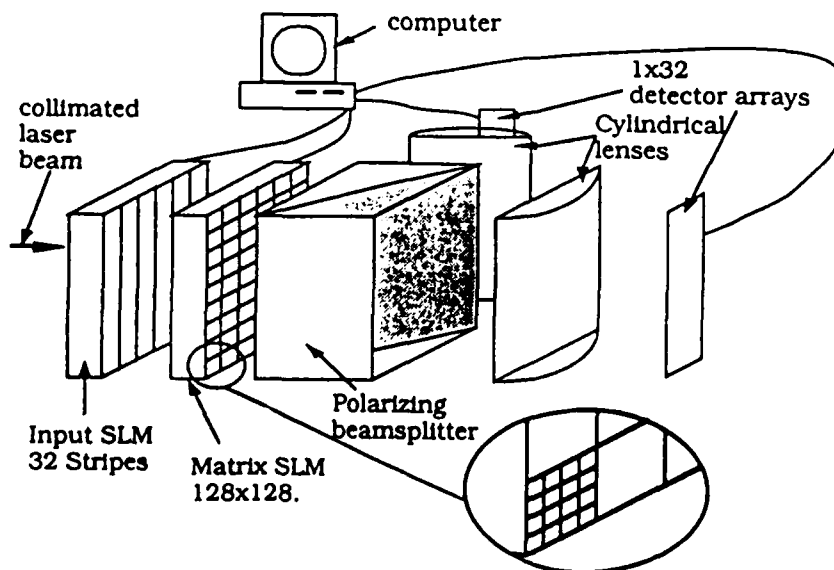
K. Johnson, University of Colorado OCS

32 inputs, 32 outputs - single layer with electronic learning

17 inputs, 10 hidden, 3 outputs - electronic backprop

Learning weights as polarization rotating pixels on LC SLM

Learning successfully compensated for optical imperfections



Compact, spatially multiplexed FLC OCM

J. Hong, Rockwell Sciences

Image classification using a photorefractive perceptron

Coherent erasure by Stokes theorem

Photorefractive erasure leads to unlearning

F. Mok, Northrup

Multiple image storage in photorefractive LiNbO_3

500 images with no crosstalk

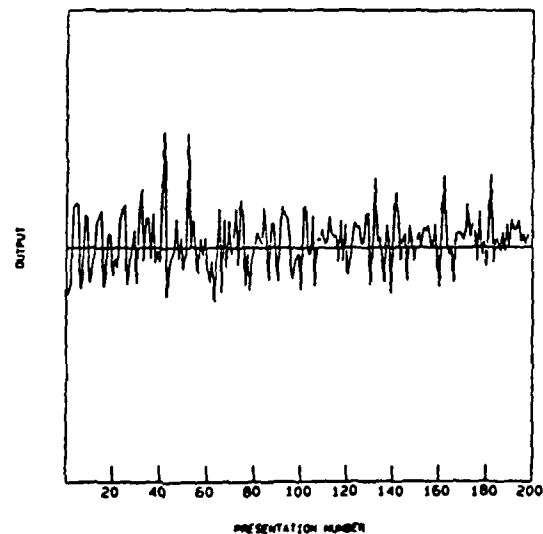
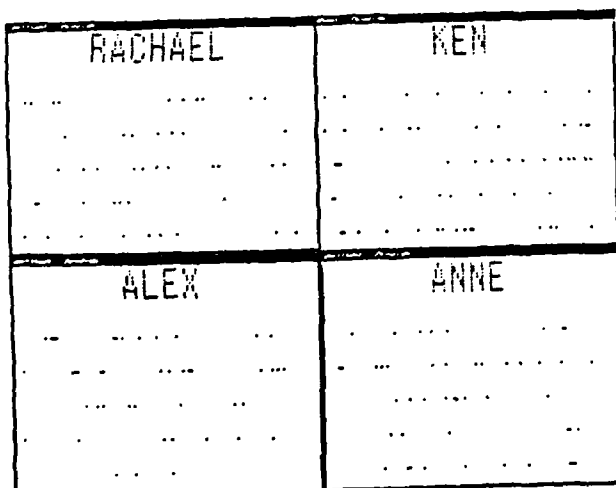
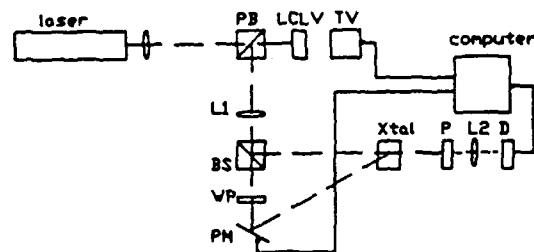
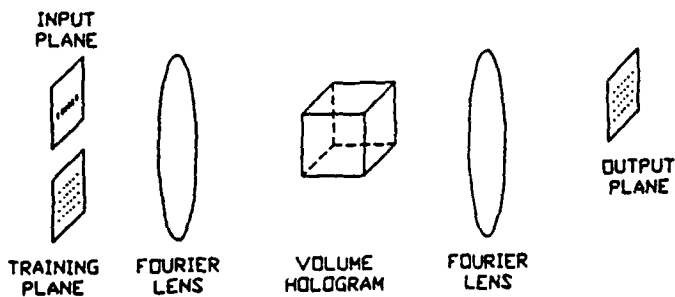
D. Brady, University of Illinois, Urbana

Optical learning in volume holograms, sampling grids

Scheduling for learning, read-write asymmetry, loading

500 input, 500 output, learned 20 associations

Perceptron learning demonstrated



Optical Synapse Technology

Photorefractive Crystals

Read-Write asymmetry necessary for learning

Cr doped BaTiO₃ - difficult to erase gratings

Hole fixing in cooled BSO

500 holograms (320x240) angularly multiplexed in LiNbO₃:Fe

Thermal fixing, exposure scheduling, 25% uniformity

.02° separation, 300:1 beam ratio

Slow rotation to eliminate fanning noise in photorefractive amplifiers

Photorefractive fiber sensor for robot arm

Winner-take-all and sequential dynamics in photorefractive resonators

Fractal sampling grids allow global interconnections

Loading of N^3 holographic degrees of freedom requires scheduled training
only have $2N^2$ control parameters

Holographic Associative Memories

Space Variant Interconnections with CGH very inefficient

$N \times N$ array of neurons requires $8N^2 \times 8N^2$ e-beam CGH

low precision interconnection strengths, use redundancy

$N=64$, $N^2=4096$, hologram $= (6.4\text{cm})^2$ with $1\mu\text{m}$ pixels

Optical disks to store synaptic weights

CGHs can be written on Sony sampled format optical disk

Holographic reconstruction writes weights onto VLSI neural network

Uses optically controlled synapses on an electrical neural net chip

Optical Neuron Technology

Sources (LEDs or LDs) vs Modulators

Silicon hybrid or GaAs monolithic

Goals

$\geq 10^4$ neurons per chip

response time 1msec $\rightarrow$ 1 μ sec $\rightarrow$

optical gain $\gg 10 \rightarrow 10^6$

power dissipation $\ll$ 1mW/neuron

Technologies

Photodetectors and Amplifiers

Photodarlington, photodiode FETs, ...

Smart Spatial Light Modulators on Silicon VLSI

PLZT

ferroelectric liquid crystal

GaAs Source - Mutually incoherent

LEDs

Surface emitting vertical cavity Laser Diodes

Surface emitting microresonator laser diodes - optically pumped

GaAs Modulator Arrays

SEEDs, Symmetric-SEED arrays, and Multi-Seeds

Heterojunction Bipolar SEEDs

Optically Addressed Spatial Light Modulators

H: α -Si photodiodes - ferroelectric liquid crystal SLMs

Photorefractive 2-beam coupling

Resonator dynamics for winner-take-all

Implications of Neural Network Theory

Learning from examples

Need enough examples to learn a functional mapping

$$m \geq \frac{64W}{\epsilon} \log \frac{64N}{\epsilon}$$

m = # examples required for confident generalization

W = # weights, N = # neurons, $1 - \frac{\epsilon}{2}$ correctly classified

Optics, huge number of interconnections,

therefore huge number of examples are required

How much dynamic range do synapses need?

Cover capacity = $2N$, with binary weights capacity = N

Binary synapse learning with directed drift algorithm

Neurons require accuracy $1/N$

Low dynamic range synapses may be good enough

Training restricted neural networks

Domain of learning must be constrained or learning is intractable

Curse of dimensionality

Higher order neural networks

Can be used for learning grammars and sequential processing

Scales very poorly in VLSI, N inputs per neuron, not 1 summed input

Optics can do quadratic elegantly

Scalability

Need to grow or prune networks to fit the task

Optics has a superabundance of resources

may allow fast learning then pruning

Some Conclusions

Optical vs Electronic neural networks

Incredible advances in electronic neural nets are foreseen.

Optics is shooting at a moving target.

Main advantage of optics is high connectivity

Ability to build huge networks, $N \geq 10,000$

What problems inherently require such huge networks?

Can such huge networks be trained?

Require enormous number of training samples

3D interconnections using volume holograms

Unique to optics

The brain is 3D.

VLSI is limited to 2D.

Allows compact realizations of huge networks.

Optical implementation of adaptive nets

Capable of learning out some imperfections

Stand a better chance for success than other optical computing paradigms.

Mismatch between theoretical models and optics.

Develop new algorithms matched to optical hardware.

Importance of biological principles.

Existence proof of the utility of the neural paradigm

Holographic style processing has no direct electronic counterpart

Applications appropriate for optical neural networks.

Image Recognition, inherently 2D problem.

Take advantage of shift invariance.

Naturally dynamical problems such as speech

Nonlinear dynamics can be matched to optical physical dynamics.

Huge problems

AI data base search

Optics needs to solve a real problem

One that electronics can not do, in order to demonstrate its viability.

OPTICAL COMPUTING NEWSLETTER

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■ ISSUE HIGHLIGHTS

Progress on optical neural networks...Calendar of events

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Workshop considers optical neural networks

What can optics do for neural networks? This was the question addressed by 39 researchers who attended the Workshop on Optical Neural Networks in Jackson, WY, Feb. 7-10, 1990. The workshop, sponsored by the US Air Force Office of Scientific Research and the Office of Naval Research, was organized by Lee Giles (NEC Research Institute, Princeton, NJ), Demetri Psaltis (California Institute of Technology [CalTech], Pasadena, CA), and Kelvin Wagner (Optoelectronic Computing Systems [OCS] Center, University of Colorado [CU] at Boulder).

The purpose of the workshop was to critically examine the status of optical neural-network research and evaluate its present and future roles, particularly as an implementation technology for neural-network models of computation. Participants included researchers in optical neural networks as well as experts in related fields such as active optical devices, VLSI implementation of neural networks, and neural-network architectures, algorithms, and theory.

Neural networks typically consist of weighted global interconnections between arrays of simple nonlinear units. Their output is usually a soft threshold version of the weighted and summed inputs from other neurons. Learning dynamics are used to evolve the interconnection weight matrices as a succession of small perturbations, usually implemented as sums of outer products. These are the essential features that must be incorporated into any hardware implementation of a neural network.

Optical techniques are being considered for the implementation of neural-network models of computation because of several unique properties of optical systems. These include the three-dimensional (3-D) topology of optical systems and the ability of optical beams to cross through one another in free space, allowing the compact implementation of global interconnect networks. In addition, the continuous analog nature of optical systems can be combined with nonlinear optical devices to implement nonlinear dynamical systems, which are a good match to neurodynamical models of computation and learning.

Optical approaches to the implementation of neural networks are usually based on one of two distinct techniques for implementing the weighted interconnections required by the neural models. The first approach, shown in Fig. 1, uses the variable transmittance of a pixel in a two-dimensional (2-D) spatial light modulator (SLM) to represent the weight of an interconnection. The second approach uses the programmable diffraction efficiency of a holographic grating to represent the weight of an interconnection. Both techniques rely on spatial broadcasting and spatial collection of the weighted outputs to complete the required matrix vector multiplication.

A potential advantage of the holographic technique, which was emphasized by several conference participants, is the ability to utilize volume holograms to store the interconnection gratings in three

dimensions, as shown in Fig. 2. This allows a tremendous density of weighted interconnections to be realized, and the use of dynamic materials (such as photorefractive crystals or organic holograms) allows the implementation of real-time learning in the optical domain. This is based on an extension of the holographic metaphor for associative memory proposed by Van Heerden and Gabor more than 20 years ago. Two key developments that distinguish modern optical neural-network research from earlier pioneering work on holographic association are the incorporation of dynamic learning algorithms and the central role played by the neural nonlinearity.

Learning systems

The most distinctive feature of neural-network models of computation is the ability to learn from experience. This is accomplished by adaptively modifying the strength of the interconnections between the neurons. In optical systems, these

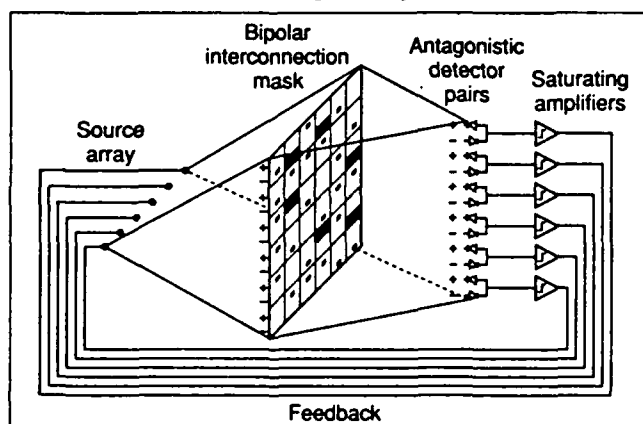


FIGURE 1. Controllable pixel transmittance allows optical light modulator to work in an optical neural network.

weights are usually represented as the diffraction efficiency of holographic gratings or as the transmittance of pixels in a SLM. Neural learning algorithms give rules for the adaptive modification of these interconnections or weights, which are almost always based on iterative outer product perturbations of the weight matrix. This can be mapped into optics as either associative holographic recording or as the product of crossed one-dimensional light modulators addressing a 2-D optically addressed SLM.

Several successful optical learning demonstrations using photorefractive crystals were presented at this workshop. John Hong (Rockwell Science Center, Thousand Oaks, CA) demonstrated the successful operation of a photoreceptive perceptron. His system uses coherent erasure to decrease the adaptive weights, where a π phase-shifted grating is written on top of an existing grating, thereby partially canceling the grating. Eung Gi Paek (Bellcore, Livingston, NJ) presented a perception learning

system that uses a photorefractive crystal to provide the adaptive weighting. The system had 250,000 input neurons and 10 bipolar outputs. His research demonstrated that a multiple-output perceptron could be implemented by multiplexing gratings in a volume medium without unwanted crosstalk. Both Paek's and Hong's systems exhibited anomalous unlearning due to incoherent erasure in the crystals after the desired pattern associations had been learned and were simply being read out.

Successful learning was also obtained in systems employing SLMs as the adaptive interconnections. Kristina Johnson (OCS Center, CU-Boulder) presented results of single-layer and multilayer learning experiments in a polarization-based liquid-crystal optical connectionist machine (see Fig. 3.). The optical connectionist machine has performed associations between 32 input and output neurons trained

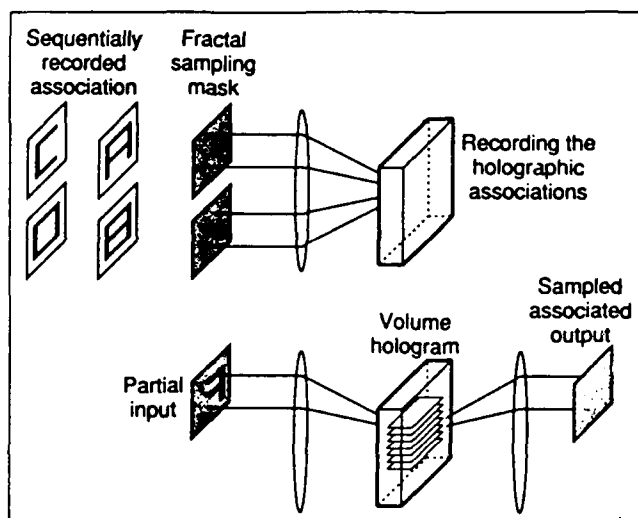


FIGURE 2. Holographic approach to optical neural networks takes advantage of volume holograms.

on 200 patterns of sunspot data to predict solar flare activity. The learning dynamics successfully compensated for several varieties of noise due to imperfections in the optics.

Nabil Farhat (University of Pennsylvania, Philadelphia, PA) presented work on Boltzmann machine learning using binary SLMs. He showed how a multilayered network can be implemented in a single layer of hardware by partitioning the weight matrix into a number of blocks representing the interconnections between different layers. He also discussed phase-space engineering, which describes his approach to designing an optical neural network. This entails the design of the path of a complex system through its state space and represents a computation as the state space evolution of the system.

Optical-synapse technology

The successful realization of optical neural net-

works is dependent upon the availability of components that can act as neurons and synapses. The optical synapses must weight the interconnections between the neurons. The ability to dynamically modify these synapses is required to implement adaptive-learning algorithms.

Holographic interconnections using dynamic volume holograms were discussed by several participants. A major difficulty with these materials is the incoherent erasure that occurs while the holograms are being read out, which results in the unlearning phenomena observed by Paek and Hong. This incoherent erasure problem in photorefractives can be alleviated by inducing a read-write asymmetry.

Henri Rajenbach (Thomson-CSF, Boulogne-Billancourt, France) presented preliminary results of hole fixing in cooled BSO ($\text{Bi}_2\text{SiO}_{20}$), which resulted in the ability to continuously read out images for several hours without erasure. This is possible because a photogenerated hologram written by the electrons is compensated by the holes, and at low temperatures the hole mobility is much lower than the electron mobility, so that a hologram written as spatial modulations of the hole density remains frozen into the crystal.

Fai Mok (Northrup Corp. Research and Technology Center, Palos Verdes, CA) presented results of multiple-image storage in $\text{LiNbO}_3\text{:Fe}$, which used thermal fixing and exposure scheduling to compensate for erasure during writing and also eliminated erasure during readout. He has successfully stored and retrieved more than 500 images of more than 60,000 pixels each, with greater than 0.01% diffraction efficiency.

Dana Anderson (OCS Center, CU-Boulder) showed winner-take-all behavior in sequential recall dynamics in multicrystal photorefractive resonators. The computation dynamics inherent to the photorefractive circuits can be applied as a very general technique for obtaining almost any dynamics, provided one has a sufficient number of modes and sufficient control over the mode interactions. Furthermore, this class of optical system is one of the few kinds of physical systems that can embed continuous distributions of neural activity processing in continuous time.

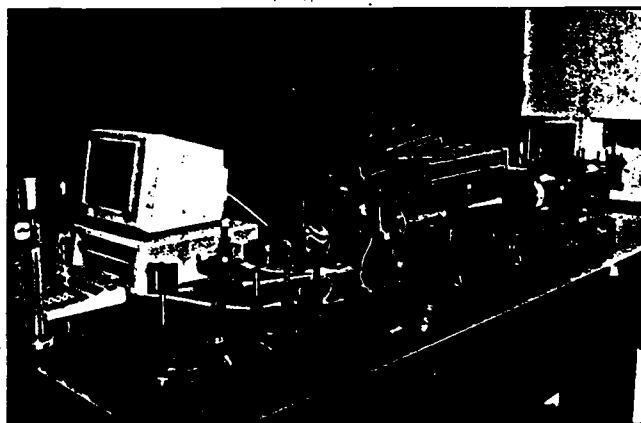
Art Gmitro (University of Arizona, Tucson, AZ) and H. J. White (British Aerospace, Bristol, UK) presented analysis of the limitations of space-variant-weighted interconnections using e-beam written computer-generated holograms for interconnecting 3-D neuron arrays on liquid-crystal light valves. They both concluded that up to about 64×64 -neuron arrays could be globally interconnected to implement a nonadaptive optical neural network using this technique. However, larger networks would be beyond the technological capabilities of this technology. This is because the size and resolu-

tion requirements of a space-variant interconnection hologram for an $N \times N$ -neuron array grow as $KN^2 \times KN^2$, where K is an oversampling factor, typically greater than 10. In addition, the accuracy of these weighted interconnects might be too low for some applications (such as neural optimizers), but it might be sufficient for optical associative memory.

Alan Yamamura (CalTech) presented new results of writing computer-generated holograms on Sony's sampled-format optical disks. Holographically reconstructed weight matrices were written onto optically programmed VLSI neural chips to control the electronic interconnect topology from the optical domain. This allows rapid reprogrammability of the interconnections to implement multilayer networks.

Optical neuron technology

Optical neurons need to sum a huge number of weighted inputs and produce a threshold output. The goals, stated in an introduction by Demetri



UNIVERSITY OF COLORADO

FIGURE 3. Polarization-based optical connectionist machine has learned from sunspot pattern.

Psaltis, are to produce devices with more than 10,000 neurons with a response time in the microsecond range, gain greater than 10, and power dissipation below a milliwatt. Although such a device capability is not yet available, several technologies appear to be approaching this goal.

Ferroelectric liquid crystals are promising candidates for implementing large arrays of low-power neurons. Garret Moddel (OCS Center, CU-Boulder) illustrated the capabilities of an amorphous-silicon ferroelectric-liquid-crystal (FLC) optically addressed SLM (OASLM) using smectic C^* and smectic A^* materials. The smectic A^* device achieves as low as a 4- μs response time for a 1000×1000 array requiring 0.1-pJ/pixel switching energy. These capabilities make this an almost-ideal device for implementing optical neurons. Further improvements can be made by including a third terminal, which his group recently demonstrated, thereby implementing a variable threshold device.

Tim Drabik (Georgia Institute of Technology, Atlanta, GA) presented recent results on a silicon VLSI chip coated with an FLC, which incorporated photodetectors and acted as an OASLM. This device may have applications as an optical neuron array or as an early vision optical preprocessor.

Another promising approach is to use optoelectronic GaAs modulators and sources such as LEDs and diode lasers driven by electronic photodetectors. Several variants were proposed for optical neurons, and their properties were compared and contrasted. Tony Lentine (AT&T Bell Labs, Naperville, IL) showed results of a 1.5-pJ switching-energy symmetric self-electro-optic-effect device. Arrays of those devices can implement loser-take-all dynamics by electrically interconnecting them in series. Although this is the opposite of the winner-take-all dynamics required in many neural models, it can be modified by following with a separate optical inversion stage.

Demetri Psaltis showed results of a 10×10 array of phototransistor Darlington-amplifier LED neurons fabricated in GaAs. LEDs were chosen instead of more-efficient diode lasers because they have no current threshold, and the power dissipation of a very large array of optical neurons can be minimized.

Implications of neural-network theory

Neural-network theory has several implications for the requirements and limitations of optical neural networks. These issues were discussed at length

during the workshop. Two specific consequences are mentioned here.

Santosh Venkatesh (University of Pennsylvania) presented results on the required dynamic range of synapses and showed that, with binary synapses, storage capacity is only reduced by a factor of two from real synapses. He presented a simple directed-drift learning algorithm for these binary synapses and concluded that low-dynamic-range optical synapses may be adequate for many applications. This, however, did not alleviate the dynamic-range requirements of the neurons, nor did it address the issue of contrast ratio or noise.

Eric Baum (NEC Research Institute) discussed the limitations inherent to learning from examples and concluded that the huge number of interconnects available in optical systems may require a huge number of training exemplars to achieve valid generalization. One suggestion to alleviate the unfavorable scaling properties of large networks was to expand or prune the networks to fit the task. He suggested that the superabundance of resources in optics may allow fast learning, followed by pruning, to achieve a minimal optical network quickly and obtain good generalization.

Kelvin Wagner
University of Colorado at Boulder
Lee Giles
NEC Research Institute
Demetri Psaltis
California Institute of Technology

Conference Calendar

NLO '90/Nonlinear Optics: Materials, Phenomena, and Devices	Kauai, Hawaii, USA	July 16-20
IEEE/LEOS Topical Meeting on Broadband Analog Optoelectronics Devices and Systems	Monterey, CA, USA	July 23-25
IEEE/LEOS Topical Meeting on Optical Multiple Access Networks	Monterey, CA, USA	July 25-27
IEEE/LEOS Topical Meeting on Integrated Optoelectronics	Monterey, CA, USA	July 30-Aug. 1
Topical Meeting on Optical Amplifiers and Their Applications	Monterey, CA, USA	Aug. 6-8
Optics in Complex Systems: 15th Congress of the International Commission for Optics	Garmisch-Partenkirchen, FRG	Aug. 5-10
Topical Meeting on Spatial Light Modulators and Their Applications	Incline Village, NV, USA	Sept. 10-12

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