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Invited

Devices for Optical Neuro Computing

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Technologies for optical implementation of neural networks are described, with emphasis on the present status and future prospect of optical neuro-devices. The quantized neural network modelling for optical implementation and several demonstrations of optical artificial hardware including static- and dynamic-optical neurochips are also discussed.

1. INTRODUCTION

Optics is very promising for building large-scale and high-speed neurocomputers because of its unique features of innate parallelism, and global and dense intercon-nection capability[1]. The future prospect of the performance of the optical neural networks is illustrated in Fig.1, as com-pared with the Si-LSI approaches. Among various optical architectures reported so far, the approach based on the optical vector/matrix multiplier using discrete devices are particularly attractive because optical integration is possible by the compound-semiconductor technologies. However, one problem is that the present neural models are not necessarily suitable for optical implementation in terms of the accuracy required for the devices. The second problem is that the technologies for optical integration is not matured.

This paper contains two topics. First, quantized learning models which permit the use of the binary-operating optical devices are proposed, followed by the experimental demonstration of 26 characters recognition by the optical hardware. Secondly, GaAs optical neuro-chips including both static and dynamic chips are described.

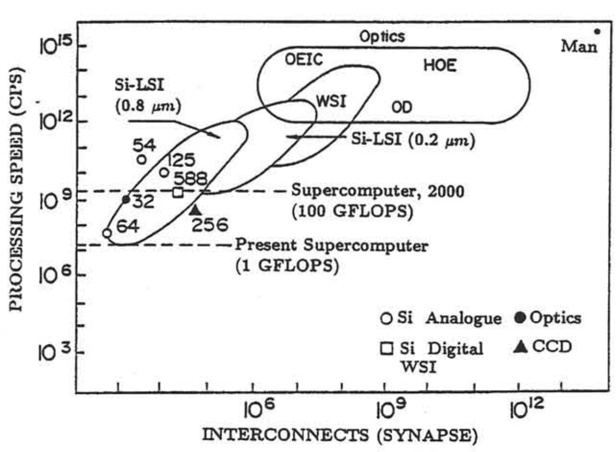

Fig.1 Present status and future trend of the artificial neural hardware.

2. QUANTIZED LEARNING MODELS FOR OPTICAL IMPLEMENTATION

2-1 Quantized Learning Rule

The profound difference between hardware- and software-implemented systems is the limitation of the interconnection weight levels in the hardware. In this context, quantized learning rules were developed for the back-propagation (BP) model[2] and Boltzmann machine[3]. As an example, the proposed learning procedure for the BP model is principally illustrated in Fig.2 and summarized as follows; (1) Start with randomly-distributed continuous weights W_{ij}, (2) Quantize W_{ij} into several discrete (quantized) levels W_{ij}, say, (-W, 0, W), (3) Address W_{ij} on the SLM and present one of the training and supervised signals to the network, (4) Calculate the error signal δW_{ij} by the conventional BP formulas, (5) Correct the continuous weight W_{ij} by adding δW_{ij} (6) Repeat steps (2)-(5) for all training signals until the connection strength pattern is converged. In this learning, the quantized weights are addressed to the optical hardware whereas the continuous weights are stored in the electronic memory. Therefore the smooth change in the weights as well as the fast optical parallel processing are achieved.

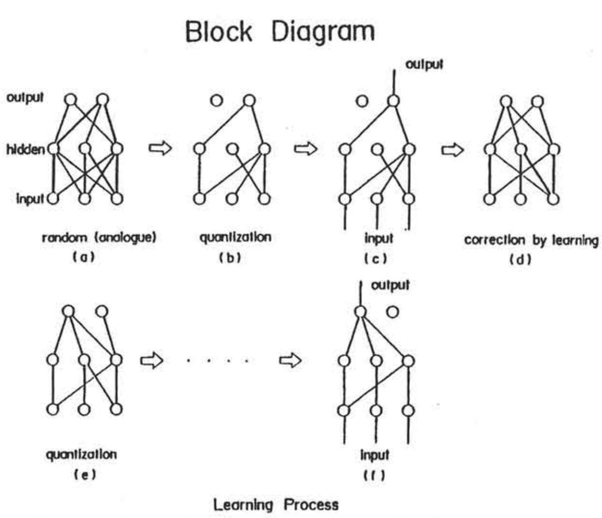

Fig.2 Learning procedure of the quantized BP model.

2-2 26 Characters Recognition by The Optical Learning Network

A schematic diagram of the optical network based on the quantized learning rule with bipolar three levels is shown in Fig.3.

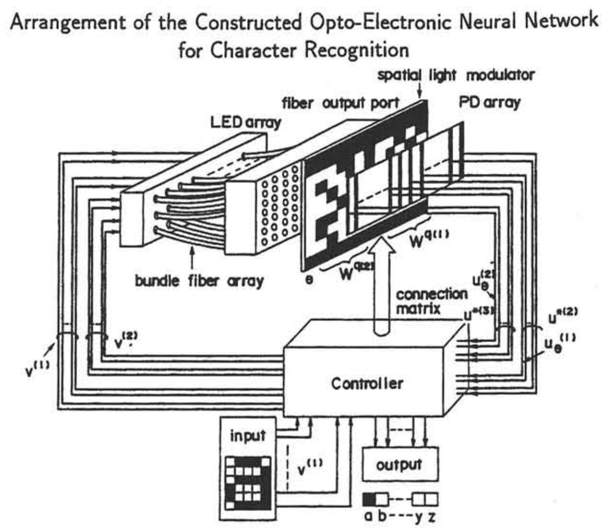

Fig.3 Constructed optical hardware for the proposed model.

The optical multiplier is constructed of 32 LEDs, a binary-liquid-crystal SLM with 32 X 32 pixels, and 32 PDs. The time-division-multiplexing technique[4] was employed to implement the three-layered BP network. We have succeeded in the recognition of 26 characters of alphabet, "a" to "z", using this learning network[5]. The network was trained so that the output neuron which takes the maxmum value among 26 neurons corresponds to the desired answer in response to the input training character. The experimental results well agreed with the computer simulations.

3. OPTICAL NEUROCHIPS

3-1 Static Optical Neurochip

Two types of AlGaAs/GaAs optical neurochips, that is, Hopfield-type and BP-type, have been developed by MBE crystal growth technique. The Hopfield-type neurochip has fully-connected 32 neurons and 3 stored memories. The recognition rate of the associative memory using this chip was well agreed with the computer simulation results[6]. The processing speed was 2.6 GCPS. Figure 4 shows the experimental layout for the 26 alphabet recognition using the newly-

Experimental Configuration

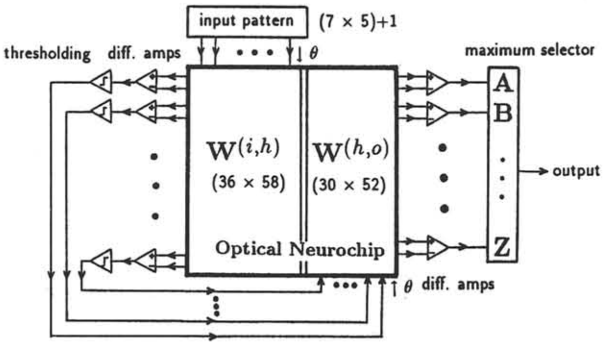

Fig.4 Layout of the newly-developed BP-type optical neurochip.

developed BP-type neurochip. This neurochip consists of 66 line-shaped LEDs, 3648 quantized synaptic interconnection elements and 110 line-shaped PDs, which are three-dimentionally integrated on a 10-mm square GaAs substrate. The AlGaAs/GaAs MQW active layers and AlAs/GaAs Bragg reflectors were introduced in the LED elements to obtain high-efficient and uniform emission. The experimental results are shown in Fig.5

Typical Experimental Results

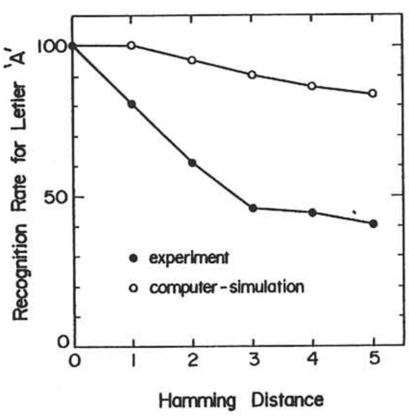

Fig.5 Typical experimental recognition rate as a function of the Hamming distance.

together with the computer simulations. It is verified that the use of the quantized synaptic weights is very helpful for optical implementation. The little discrepancy between them will be decreased by the improvement of the flip-chip bonding technique.

3-2 Dynamic Optical Neurochip

In order to develop a dynamic optical neurochip, we propose the use of a sensitivity-variable photodiode[7], as shown in Fig.6. This device consists of a MOS-type PD and a pn junction. The MOS-PD works as a SLM because the depletion depth is varied by the gate voltage and then the absorption rate is modulated. This device can be employed as an nonvolatile SLM by using the poly-silicon film as the gate material, and then the on-chip learning is possible. The photocurrent generated in the depletion layer in summed up through the pn junction and the metal-wired dendrite.

The computer simulation results are shown in Fig.7. The optical crosstalk and signal to noise ratio are plotted as a function of the neuron number which can be integrated. The parameter is a gap between the LED array and the sensitivity-variable photodiode array for the optical crosstalk (solid curves), and bandwidth for the signal to noise ratio (dotted curves). When the

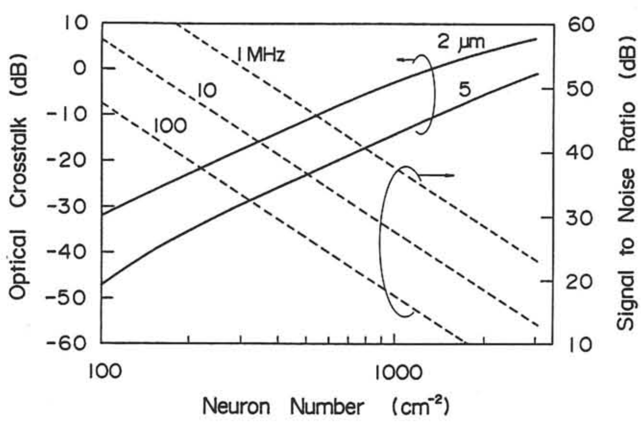

Fig.7 Calculated optical crosstalk and signal to noise ratio as a function of the neuron number.

bandwidth is 1 MHz, the neuron number is mainly limited by the optical crosstalk. It is found that the maxmum number of neurons is more than 2000 neurons/cm^2 for the BP learning networks because the permitted optical crosstalk is about -5 dB[8]. And the possible neural processing speed is estimated to be 1 to 100 TCPS.

4. CONCLUSION

The optical neural network technologies recently developed in our laboratory have been reviewed. The proposed quantized models was verified to be useful for optical implementation. The optical neurochips are expected to play an important role for the large-scale and ultra-fast hardware.

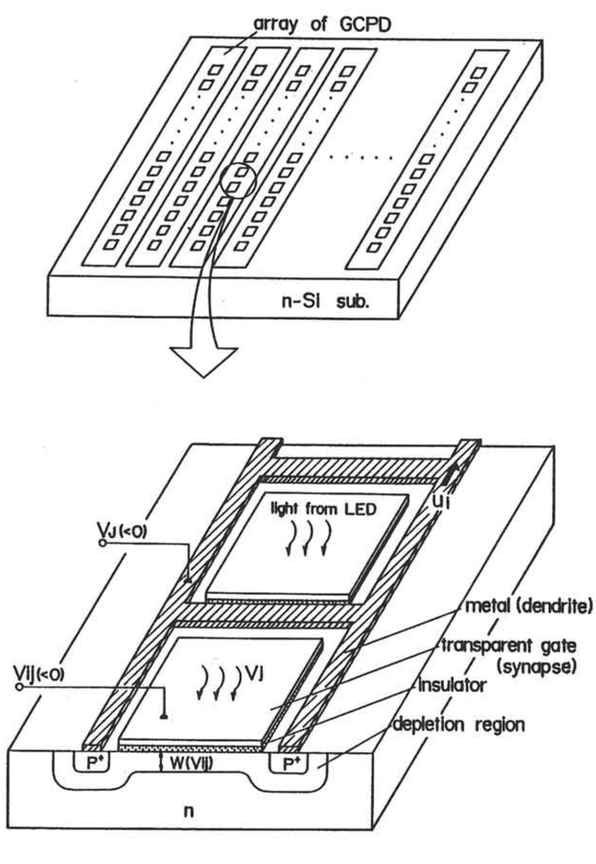

Fig.6 Dynamic optical neurochip using a sensitivity-variable photodiode array.

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