〔RESEARCH〕

High-Speed Learning System for Large-Scale Optical Neural Network

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We constructed a large-scale optical neural network system with high-speed learning operation. The optical-electronic hybrid system performs learning and recalling phases by two-dimensional optical means for handling images without scanning and pixeling. The high-speed learning capability was implemented using optical parallel calculation technique on the system. We demonstrated training for recognition of three human faces using the experimental system according to the back-propagation algorithm. The system had successfully learned the three human faces with 158 iterations of the 96ms learning cycle.

§ 1 Introduction

Artificial neural networks have attractive features, massive parallel processing and learning capability. Among many applications of neural networks, a face recognition problem is important in security systems. Recognition of facial characteristics is known as one of identification techniques. It is, however, a difficult task and to require long training time, because a face image has a huge amount of information. Large-scale and high-speed systems are required to solve this problem.

We have been proposing and demonstrating an optical learning neural network with a Pockels readout optical modulator (PROM), which operate at high speed not only recall procedure but learning phase[1]. The PROM is an optically addressable spatial light modulator with high resolution, memory, addition and subtraction abilities[2]. In a learning phase, using of these features for the weight interconnection device and a blue LED array for the error signals, the optical system that did not depend on the video signal became possible[3]. However, a CCD camera used for the recall procedure brought a bottleneck of operation speed in the complete system.

In addition, about the usual operation of the PROM, a positive mode is used which the writing with blue LEDs at applied voltage of 5kV and readouting with a red LED at that of 0kV. Therefore whenever the recall procedure and the learning phase were repeated, it was necessary to switch the high voltage. This switching time was one of the factors to limit the operation speed.

Then, to improve the operation speed of the system we replace a CCD camera with a photo detector array (PDA) and use the PROM without switching of high voltage.

In this paper we describe the principle, implementation and learning experiment of the optical neural network system. In Section 2, the principle of an optical learning neural network operation with a 2-D structure and a spatially coding method of optical information are reviewed. In Section 3, we describe an implemented system based on optical learning technique. In Section 4, experiments of training procedure are demonstrated.

§ 2 Principle of Optical Learning System

Operation of the neural network is classified two procedures that are recall and learning. Recall procedure is to obtain arbitrary output from input data, which is determined by an interconnection weight matrix.

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Learning phase is to modify the interconnection weight matrix so as to obtain a desired output. **Figure 1** shows a schematic illustration to explain the principle of optical recall with a 2-D structure in a two-layer. For the recall process in a 2-D neural network, I_{ij}, the (i, j)th element of an input image is treated as a 2-D optical matrix data. The (k, l)th output O_{kl} of the two-layer is calculated by

$$O_{kl} = f\left[\sum_{j}\sum_{i}(W_{ijkl} \times I_{ij})\right], \quad (1)$$

where f [] is a nonlinear function and W_{ijkl} is the interconnection weight tensor between the input and the output matrices. In optical implementation, a multiple input image is obtained by a multiple imaging optical system. The element of the multiple input images (I_{ijkl}) is overlapped with that of the weight tensor and $W_{ijkl} \times I_{ij}$ is calculated. Then local accumulation is done inside the local matrix elements. Finally, a nonlinear function is executed to complete the recall operation.

Figure 2 shows the principle of optical parallel computation in the learning phase. In the learning process, the new weight $W_{ijkl}(t+1)$ is obtained by addition of an updating weight value ΔW_{ijkl} to the old weight $W_{ijkl}(t)$:

$$W_{ijkl}(t+1) = W_{ijkl}(t) + \Delta W_{ijkl}. \quad (2)$$

In typical neural-network learning algorithms such as the back-propagation and the delta rule, the update value is given by the outer product,

$$\Delta W_{jikl} = \alpha(\delta_{kl} \times I_{ij}), \quad (3)$$

where δ_{kl} is an error signal and α is a learning coefficient. The definition of the error signal depends on the learning algorithms. The update value is calculated by superposing a multiple images with an error-signal matrix. This update value is added optically to the weights, and then the new weight $W_{ijkl}(t+1)$ is obtained.

In our neural network model, the weight-tensor and the error-matrix elements can have both positive and negative values. However it is difficult to represent negative values optically. Therefore, the weight-tensor and the error-matrix are spatially separated into positive and negative parts. The basic calculations in neural network, which is the inner products, the outer-products and the addition of the update value, are executed individually in positive and negative parts. In recall procedure, the final output value is obtained by subtracting the negative part from the positive part.

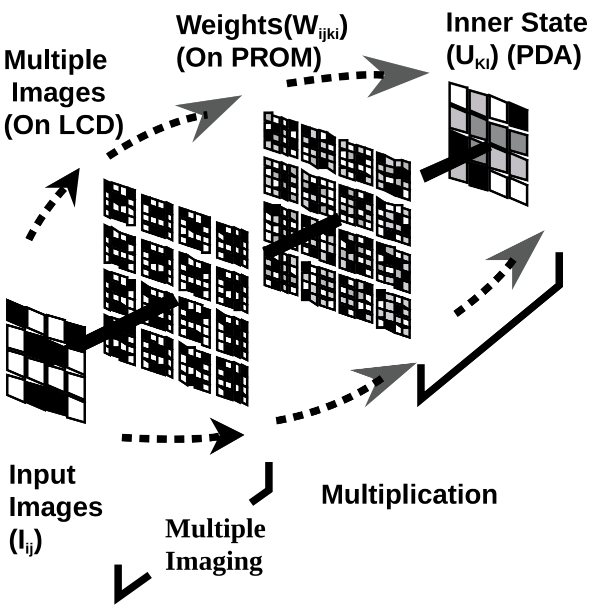

Fig.1 Schematic illustration of 2-D optical recall procedure.

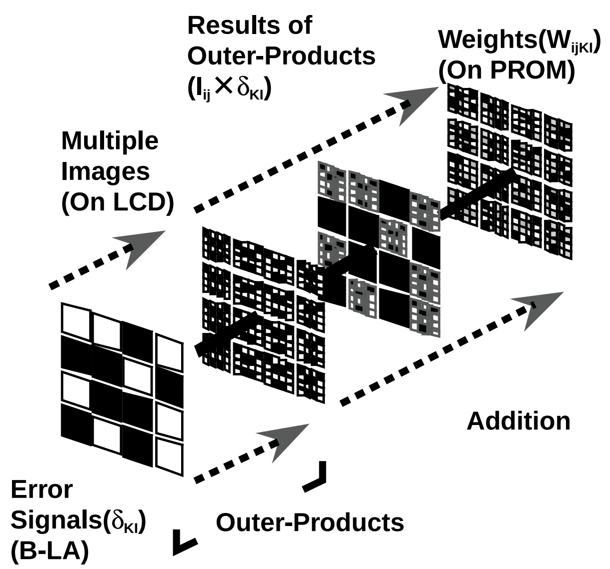

Fig.2 Schematic illustration of 2-D optical learning phase.

§ 3 Implementation of Optical Learning System

Functions of the optical system consist of four main operations. Two functions, matrix-tensor multiplication and local accumulation, are calculated in the recall procedure. Other two, matrix-matrix outer products and addition learning signals to the weight tensor, are executed at the learning phase.

Figure 3 shows the schematic diagram of the system. The optical system uses an electrically addressed liquid-crystal display (LCD), the PROM, which is an optically addressable SLM, a blue LED array, a red LED and the PDA.

The multiple image (input tensor I_{ijkl}) of an input image (I_{ij}) is displayed on the LCD during the recall procedure and the learning phase.

In the recall procedure, the readout light from a red LED is spatially modulated by the transmission of each element of the input tensor on the LCD. The light is then further modulated by the weight tensor W_{ijkl} that has been memorized on the PROM, which products between each element of I_{ijkl} and W_{ijkl}. The weight-tensor elements can have both positive and negative values. The resultant tensor image is detected and summed locally by the PDA. The subtracting the negative weight areas from those of positive areas is done in the computer. A nonlinear operation *f(x)* is also calculated in the computer.

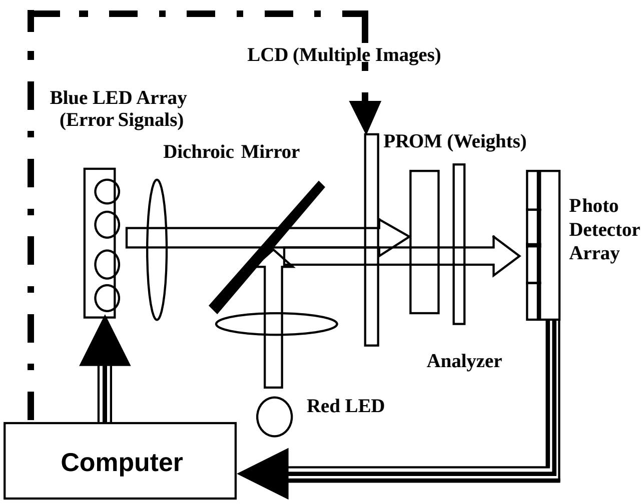

Fig.3 Schematic diagram of the optical-electronic hybrid neural network system.

In the learning phase the error signal δ_{kl} is calculated in the computer and the error-signal matrix is displayed by the blue LED array. The error signal elements can have both positive and negative values, too. Therefore, error signals are spatially separated into positive and negative parts concerned with the weight tensor. Each elements of the blue LED array are set to overlap optically with each image of multiple images. And then the outer-product ($\delta_{kl} \times I_{ij}$) of the error signal δ_{kl} and the input matrix I_{ij} are obtained. These results are added directly to the weights on the PROM as the updating values ΔW_{ijkl}. The sensitivity of the PROM and the writing time determine the learning coefficient of this system. The computer controls the writing time.

Four-f imaging optics aligns these devices (the blue LED array, the LCD, and the PROM). The position of the input multiple image elements are set to overlap each element of the error-signal matrix, the interconnection weight tensor and the local accumulation area on the PDA. In this alignment procedure, pixel-to-pixel matching is not necessary. Additionally, the alignment of the multiple input images and the learning signals to the weights on the PROM is achieved automatically.

§ 4 Experiment Results and Discussions

We prepared three human face images for training experiments, which is detected by a CCD camera under the same condition. An implemented neural network in the experimental system has a hybrid three-layer structure for employing a back-propagation learning algorithm[4]. The neural network consists of an input layer, a hidden layer, an output layer and interconnections between them. The interconnections from the input to the hidden neurons are implemented on the optical system. An array of 4×4 local areas in the output plane of the optical system is used to realize eight neurons in the hidden layer. The output layer has three neurons and the interconnections from the hidden layer to the output layer are calculated in a computer because of a small number of interconnections. The number of input neurons is approximately 60×60 pixels and the total number of the connections of the optical system is about 32000.

The training started from the state in which no weights were written on the PROM. In practice, actual initial weights were small and random values because of ununiformity of the devices and the optical system. One of the teaching signals, which corresponds to the training pattern, is set to be 1.0 and others 0.0. Because of on-line training, the weights are modified for all training patterns. The training is continued until the total error is less than 0.1.

Figure 4 shows the learning curve of the on-line training. The total error is a summation of the difference between the outputs and the teaching signals corresponding to the every training pattern. The total error became less than 0.1 after 158 iterations. In 15.2sec, we were able to train the face recognition task with three facial images. The one step time that includes one recall process and one learning phase is 96msec. The details of the 96msec are 3msec of writing learning signals to the PROM by the blue LED array, 1msec of detecting matrix-tensor multiplication by the PDA, 90msec of displaying the multiple input images on the LCD and other 2msec.

The writing time of the blue LED array is depends on sensitivity of the PROM and the irradiation optical power of the blue LED. To reduce the witting time, optimizing of the wavelength and optics of the LEDs are required. The detecting time of the PDA is concerned with an analog to digital converting board in the computer. By introducing high-speed parallel electronic circuits, the operating time of the board and the computer is shored. Because the entire majorities at the operating time hang to display data, further speed-up can be achieved by changing the liquid crystal display device to a high-speed device. For example, a feroelectric liquid crystal display works under 1ms with changing one frame with 256×256 pixels. Therefor the total operation time with several milliseconds is possible in near future.

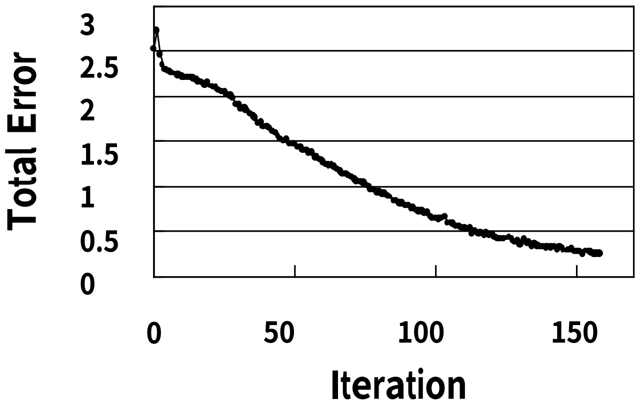

Fig.4 Learning curve of three human face recognition.

§ 5 Conclusions

A large-scale optical neural network with high-speed learning operation is implemented, and the system had successfully a training experiment for three human faces by the use of the back-propagation learning algorithm. In a typical one step time that includes one recall process and one learning phase was 96ms. The improvement of devices is expected to operate with several milliseconds.

§ 6 References

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