Classification of hand-written digits by variable OIP

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In today's highly information-oriented society, the workload of data processing is dramatically increasing. We investigate Optical Neural Network (ONN) as a potential technology for higher-speed processors with lower energy consumption. In this report, we developed a novel ONN processor that expedites quick switching of input and processing by using a unique configuration with a liquid crystal light modulator. The capability of the processor was shown by achieving high classification accuracy on the MNIST dataset.

1. Introduction

Artificial Intelligence (AI) has made notable advancements in recent years. In 2023, AI technology capable of generating content (generative AI) was developed and widely implemented, enhancing this trend. These AI technologies are supported by processors such as CPUs and GPUs, and their computations are performed electrically. The development and popularization of such technologies will continue to accelerate in the future, dramatically increasing the amount of data to be electrically computed. To sustain such an advanced information society, the development of processors with enhanced speed and reduced power consumption is imperative.

Optical computing, which employs light to execute computational operations, has been studied for over five decades as a prominent candidate, but has yet to be implemented in practice. However, recent advances in microstructure fabrication technology and optical modulation devices enable more precise manipulation of light, enhancing the feasibility of optical computing. In particular, the use of light in AI operations is recently expected to lead to the realization of high-speed and low-power-consumption processors.

Neural networks composed of light, called optical neural networks (ONNs), have mainly been implemented by waveguides based on silicon photonics[1)]. On the other hand, the ONNs that we are investigating utilize the propagation and diffraction of light in free space to perform image processing at ultrahigh speed[2)]. In this paper, we refer to this type of processor as an Optical Information Processor (OIP). We report that the OIP with a tunable light modulator achieves high accuracy in the classification of MNIST, which is a common task for AI evaluation.

1 : Advanced Research Core

2 : Technical Center for Fundamental Technologies

3 : R&D Strategy Center

2. Configuration of ONN

Figure 1 shows the concept of a conventional neural network and a schematic diagram of our ONN. Both networks consist of an input layer, intermediate layers, and an output layer. Neurons in each layer are interconnected with those in neighboring layers. During the operation, processing data passes from the input layer to the output layer, obtaining operation results on the output layer. In the case of image processing, the input data is image data, and the results, such as classification, detection, and super-resolution, are obtained from the output.

The ONN we are investigating realizes a neural network by the propagation of light, modulating the intensity and the phase of the light by optical modulation elements. The input data is loaded as a wavefront composed of an intensity distribution or a phase distribution from the input layer using an intensity mask or a phase modulator, respectively. As the modulated wavefront propagates to the intermediate layer, the distribution of intensity and phase changes due to diffraction. The light modulator used as the intermediate layer further modulates the phase distribution. Such changes of phase distribution by the light modulator and the subsequent diffractions are repeated and the final intensity distribution of the light forms on the output layer as the calculation result.

The phase modulation of each intermediate layer is designed in advance to achieve the desired task in a training process that includes the light propagation simulation.

3. Feature of our OIP

One of the features of our OIP is the use of visible light, which makes it possible to use a standard laser diode as the light source and a CMOS sensor or photodiode as the output, enabling low-cost, compact, and high-speed processing. It also allows us to directly input and process information that can be discerned by human vision. However, the need for high precision in the fabrication and the alignment of the optical elements has been preventing

Abbreviations, Acronyms, and Terms.

ONN—Optical Neural Network
Neural network that employs the use of light as a medium for data transmission.

OIP—Optical Information Processor
Processor that process information using light

LCoS—Liquid Crystal on Silicon
Liquid crystal device that modulates and reflects light

SLM—Spatial Light Modulator
Device that modulate the spatial distribution of intensity or phase of light

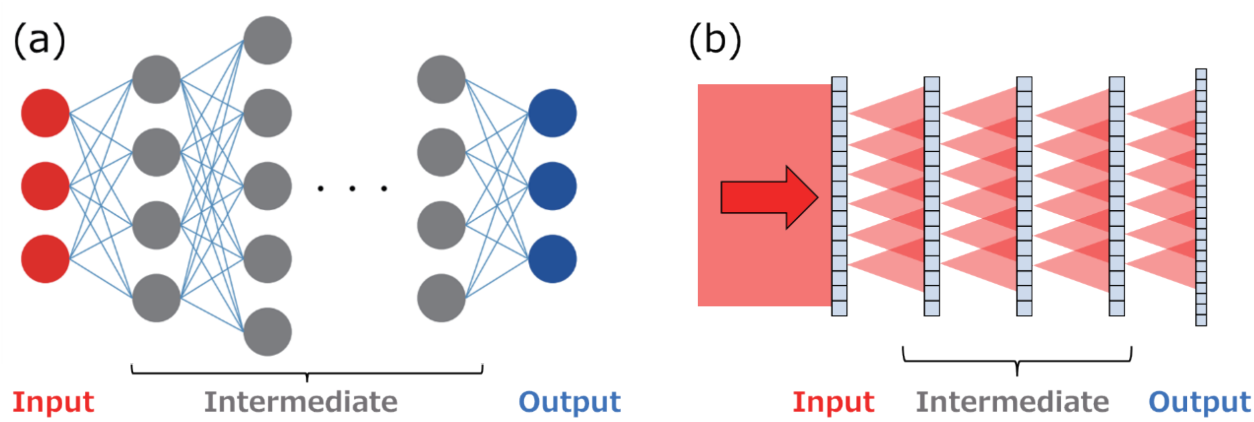

Fig. 1. Conceptual diagrams of (a) a conventional neural network and (b) the optical neural network of this study.

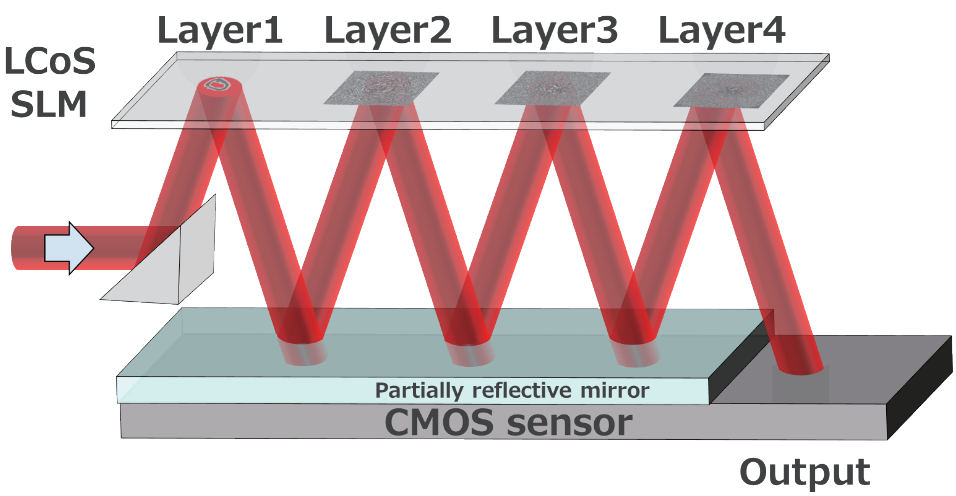

Fig. 2. Overview of our variable optical information processor.

the realization of OIP in the visible wavelength. We have newly developed a unique configuration using a reflective liquid crystal spatial light modulator (LCoS-SLM), which enables the implementation of OIP in the visible wavelength.

4. Implementation of variable OIP

An overview of our OIP is shown in Figure 2. The incident light ($\lambda = 640$ nm) from a laser diode is introduced into the processor through a prism. The processor consists of a CMOS sensor with a partially reflecting mirror attached and an LCoS-SLM installed in parallel, facing each other. The laser light is reflected and propagates between these two elements. Four areas of Layer 1 to Layer 4, designated as modulation layers, are defined in the LCoS-SLM, each of which modulates the phase of the light as the light is reflected. A partial reflection mirror attached to the CMOS sensor transmits 10% of the light and leads it to the CMOS sensor. This configuration

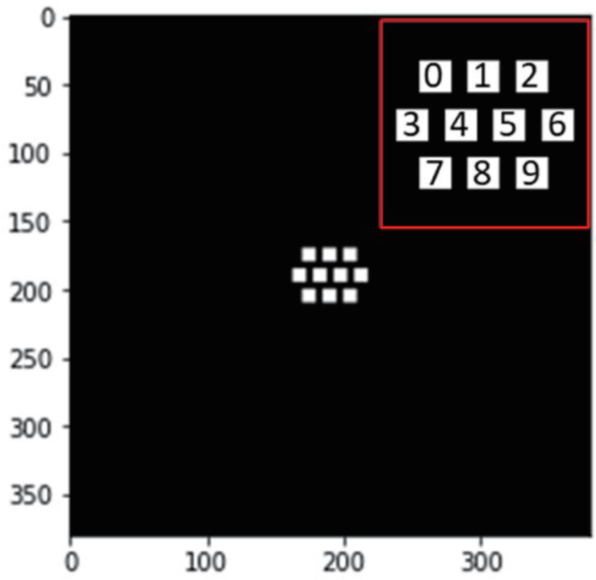

Fig. 3. Ten areas at the final detection plane.

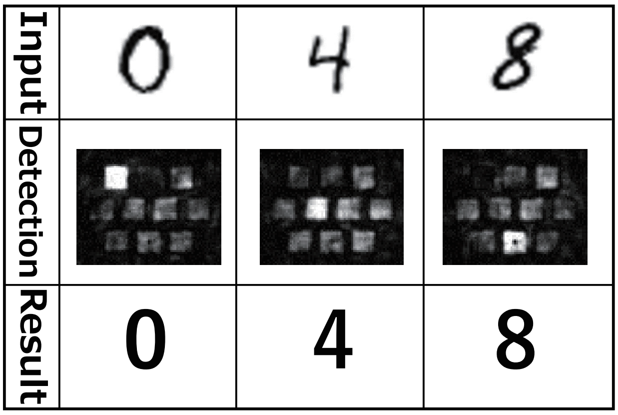

Fig. 4. Examples of intensity distribution at the detection plane and the classification result for each input data obtained in the experiment.

enables real-time monitoring of the light intensity distribution in the middle of the propagation between the layers as well as the final output.

Its simple configuration with two main optical elements makes it easy to fine-tune the setup. It also has a big advantage of switching between various tasks with a single device, since the phase modulation is implemented using a variable modulation device.

5. Learning and testing with MNIST dataset

MNIST[3)] is an image data set of handwritten numbers, which is widely used for training and evaluation in artificial intelligence. In this study, 47,995 of the 60,000 MNIST training data were used for training, and the remaining 12,005 were used for validation. The input image data were converted from the original 28×28 pixels to 380×380 pixels and then embedded on the wavefront as the phase distribution by Layer 1.

The bandlimited-angular spectrum method[4)] was used to simulate the changes of the intensity and phase distributions during optical propagation.

As shown in Figure 3, ten regions were defined on the output plane, with each region corresponding to each classification class. The pattern of phase modulation in each layer was trained so that the light intensity in the region corresponding to the correct class showed the highest for each training data. For the test, the class corresponding to the region of the highest intensity in the output plane was recognized as the classification result for each input data. It was estimated from simulations that 97% MNIST classification accuracy can be achieved with our ONN configuration.

To evaluate the classification accuracy on the actual device, the modulation patterns of Layer 2 to Layer 4 obtained by the above training were applied to the LCoS-SLM, and a total of 1000 images (100 images × 10 classes) were classified. Figure 4 shows examples of the light intensity distributions in the output plane of the experiment for several inputs with the phase modulation pattern obtained by the training. As a result, a high classification accuracy of about 95% was obtained on the actual device.

6. Conclusion

We reported the current achievements of our image processing technology using ONN, which obtains enough high accuracy experimentally (95%) to be as close as that of simulation (97%). This achievement is expected to be applied to practical tasks such as visual inspection and anomaly detection at various sites such as factories or infrastructures, which would support energy-saving and high-speed processing in the advanced information society.

Reference

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