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A MZI-based optical neural network for image classification

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In recent years, with the expansion of information, artificial intelligence technology has been developed and used in various fields. Among them, optical neural network provides a new type of special neural network accelerator chip solution, which has the advantages of high speed, high bandwidth, and low power consumption. In this paper, we construct an optical neural network based on Mach–Zehnder interferometer. The experimental results on the image classification of MNIST handwritten digitals show that the optical neural network has high accuracy, fast convergence and good scalability.

Keywords: optical neural network, image classification, Mach–Zehnder interferometer.

1. Introduction

In recent years, artificial intelligence technology has developed rapidly, emerging in various fields of social life. Artificial intelligence technology has promoted a new round of industrial transformation and gradually become a new focus of international competition. Among them, deep neural networks have solved a series of problems in various fields, such as image analysis [1], natural language processing (NLP) [2], physics [3], chemistry [4], and medicine [5].

The development of deep learning methods and technologies is inseparable from three major factors of data, algorithms, and computing power. The processing of data and the realization of algorithms require the support of chip technology on the application side. Theoretical tools underpinning deep learning have been developed for decades, and recent resurgence has been driven by significant increment in availability and computing power on large training datasets and the ability to train networks on graph process units (GPUs) [6]. In order to handle more complex problems and achieve higher network accuracy, devices with high speed, low power consumption and smaller package are required. This has led to the development of specialized hardware for optimizing neural network inference [7,8] and training [9].

However, as the information needs to be processed increases exponentially, the complexity of deep neural network increases dramatically. Though traditional electronic analog cross arrays based on CMOS gates or memory resistors have better performance, but as analog electronic devices, they have calibration problems and limited accuracy. This could not meet the requirements for processing such large amount of data and information [10]. Optical neural network chip provides a new type of special neural network accelerator chip solution, which uses the change of light parameters to perform operations. Compared with electronics, photonics has the advantages of high speed, high bandwidth, and low power consumption [11,12]. Optical neural network (ONN) chip could achieve about two orders of magnitude faster than traditional electrical chips, and the power consumption is about two orders of magnitude lower [13]. Photonic integration can greatly reduce the size of devices or modules, which is currently a hotspot in international research and has great potential of significance for the application of artificial intelligence in the near future [14-17].

In this paper, we construct an optical neural network based on Mach–Zehnder interferometer (MZI). The performance of the ONN is evaluated through a specific image classification problem, which shows the great potential for its usage as an alternative hardware solution for the acceleration of deep neural network in the near future.

2. Architecture

A typical universal optical device is a rectangular multiport interferometer mesh, in which the N-dimensional vector is represented by a set of modes arranged in N single -mode waveguides [18-20]. Cascaded MZI arrays are used to implement weight calculations for optical neural network, and the basic unit is composed of MZI device, as shown in Fig. 1(a).

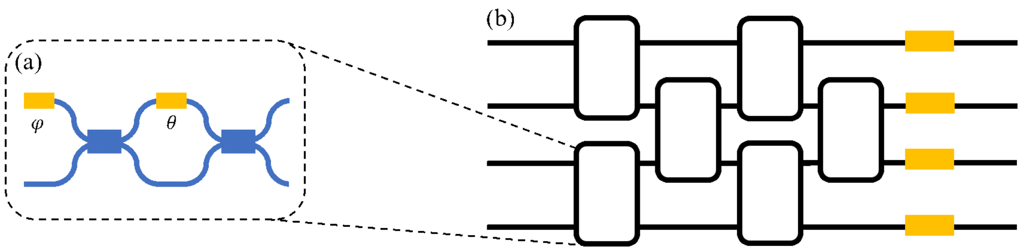

Fig. 1. (a) MZI computing unit and (b) optical neural network structure.

The MZI computing unit consists of an optical waveguide, a 3 dB coupler, an internal phase shifter, and an external phase shifter. The internal phase shifter could change the amplitude of the transmitted light, and the external phase shifter could change the phase of the transmitted light. The transmission matrix of the MZI computing unit is a second-order unitary matrix that [21-23]

$$U(\theta, \varphi) = i\exp\left(\frac{i\theta}{2}\right)\begin{bmatrix} \exp(i\varphi)\sin\frac{\theta}{2} & \cos\frac{\theta}{2} \\ \exp(i\varphi)\cos\frac{\theta}{2} & -\sin\frac{\theta}{2} \end{bmatrix} \tag{1}$$

where θ is the phase shift value of the internal phase shifter, and φ is the phase shift value of the external phase shifter. The required range is $0 \leq \theta \leq \pi$ and $0 \leq \varphi < 2\pi$.

The transmissivity of the MZI device is expressed as

$$t = \cos^2\left(\frac{\theta}{2}\right) = |U_{12}|^2 = |U_{21}|^2 \tag{2}$$

while the reflectivity is expressed as

$$r = \sin^2\left(\frac{\theta}{2}\right) = 1 - t = |U_{11}|^2 = |U_{22}|^2 \tag{3}$$

Two extreme cases would occur at $\theta = \pi$ and $\theta = 0$. When $\theta = \pi$, the MZI achieves "bar state". While $\theta = 0$, the MZI achieves "cross state".

By adjusting the MZIs with a certain topological structure, its transmission matrix is multiplied to realize $N \times N$ unitary matrix [24]

$$U = D\left(\prod U_{m,n}\right) \tag{4}$$

where $U_{m,n}$ is an N-dimensional matrix:

$$U_{m,n} = \begin{bmatrix} 1 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & i\exp\left(\frac{i\theta}{2}\right)\exp(i\varphi)\sin\frac{\theta}{2} & i\exp\left(\frac{i\theta}{2}\right)\cos\frac{\theta}{2} & \dots & 0 \\ 0 & \dots & i\exp\left(\frac{i\theta}{2}\right)\exp(i\varphi)\cos\frac{\theta}{2} & -i\exp\left(\frac{i\theta}{2}\right)\sin\frac{\theta}{2} & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 0 & \dots & 1 \end{bmatrix} \tag{5}$$

and D is an N-dimensional diagonal matrix, and the module of its diagonal element is 1, which can be realized through the phase shifter array. Figure 1 (b) shows an example of $N = 4$ input with rectangular distribution structure diagram composed of cascaded MZI.

Software frameworks are needed for simulation of such architecture. Neurophox is a typical representative based on MZI meshes written in Python/NumPy that is programmable chip-level simulation platform for nanophotonic neural networks [21]. Neurophox provides different levels of simulation for simulating photonic neural networks: the simplest function allows manipulating the arrangement and properties of individual phase shifters on the analog chip, and the most complex level provides a Keras-like API to design photonic neural networks by stacking network layers.

Universal unitary photonic devices can perform arbitrary unitary transformation on multi-port coherent light input, which provides a promising hardware platform for fast and efficient machine learning. This framework solves the problem of training general photonic devices composed of tunable beam splitter grids to learn unknown unitary matrices. If the phase shift is randomly initialized, the local interaction characteristics of mesh components limit the authenticity of the learning matrix. This framework also embeds various model frameworks in a standard rectangular grid canvas. The experimental results of the developer show that the scalability and training speed are significantly improved even in the presence of manufacturing errors.

Optical nonlinearity works by converting a small portion of the input optical signal into an analog electrical signal that is used to intensely modulate the original optical signal without slowing down the processing speed. This scheme allows for fully nonlinear on-off contrast in transmission at a relatively low optical power threshold and eliminates the need for additional light sources between each layer of the network [24]. In addition, the activation function can be reconfigured by electrical bias, allowing it to be programmed or trained to synthesize various nonlinear responses. Using numerical simulations, it is proved that the activation function significantly improves the expressive ability of photonic neural networks, which can perform well in the benchmark machine learning task-image classification.

3. Results

We designed an ONN of $N = 8$ input with the structure shown in Fig. 1 for a more complex task of classifying MNIST handwritten digit datasets [25]. As shown in Fig. 2, the MNIST dataset contains grayscale images of ten handwritten numbers from 0 to 9, each with a size of 28×28 pixels.

The experiment uses the Neurophox simulation framework and is programmed by Tensorflow, which computes gradients using automatic differentiation. This paper adopts a subset of 60,000 images in the dataset to pass through the network in 500 batches in each training epoch. The remaining 10,000 pairs of image labels are used to form a test dataset. The on-chip backpropagation method may also be faster for gradient computation than other training methods, while the Adam update rule, which is commonly used in machine learning, outperforms the standard stochastic gradient descent method in the training of a single network. If you store gradient measurements of phase shifts during training, you can apply adaptive update rules using continuous gradient measurements for each tunable component in the mesh. Such a process requires minimal calculations and can be used as a physical test simulated in an experiment. For a bilayer network with $N = 8$ Fourier components, the network is parameterized using $2 \times N^2 \times L = 256$ ($L = 2$, stands for the number of layers) free parameters. Reprogrammable electro-optical nonlinearity [22] (or any ReLU-like optical nonlinearity tunable to a linear region in general) allows programming or calibration of multilayer photonic neural networks using our parallel approach. Crucially, this means that it can compute inputs for the entire ONN rather than every layer, and program the columns of all mesh networks sequentially throughout the device, programming any desired operator. We now demonstrate the use of this protocol in our particular analog ONN to correct for significant drift.

Figure 2 shows the experimental results. Figure 2(a) compares the classification accuracy of the training dataset (blue) and the test dataset (red). Figure 2(b) compares the cross-entropy loss function curve during optimization, with a blue curve for the training dataset and a red curve for the test dataset. We observe significant improvements in ONN performance during and after training with nonlinear activation functions.

The accuracy of training data set is 98.6%, and that of testing data set is 96.14%. The cross-entropy loss of the training and test datasets is 1.55% and 14.85%, respec-

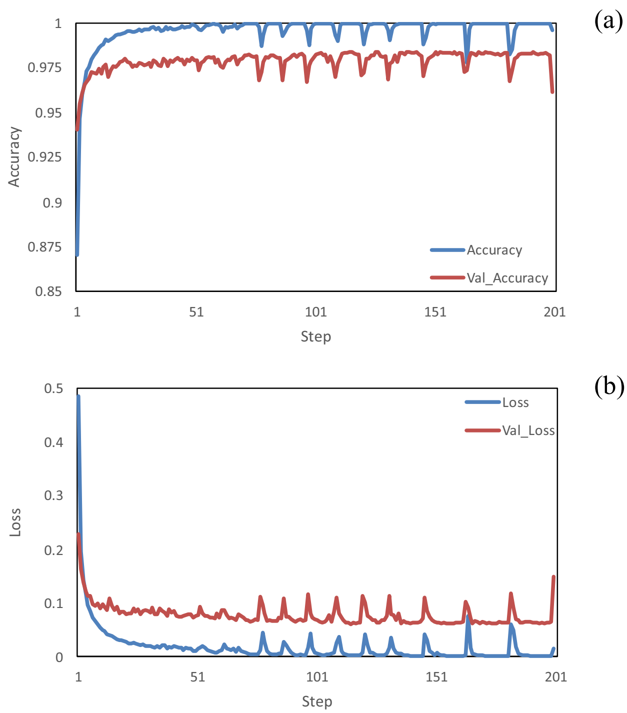

Fig. 2. (a) Accuracy and (b) loss function curve.

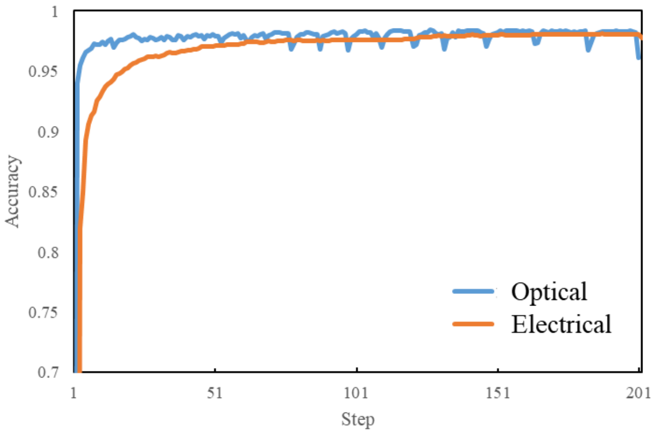

Fig. 3. Accuracy comparison of optical and electrical methods.

tively. The high accuracy reveals an excellent performance of the ONN chip, which may be of great help to its potential usage in the near future.

We also compare the test accuracy of optical and electrical methods. The electrical method uses the same number of layers and nodes as the optical method, but the number of parameters is reduced to $N^2 \times L = 128$. The comparison result is shown in Fig. 3.

From Fig. 3, it can be concluded that the accuracy of the optical method and the electrical method are finally stable at about 97%. Both of these two methods show a high accuracy. However, the optical method has better convergence than the electrical method, while the electrical method has better stability and less fluctuation than the optical method. The different performance of these two methods may be due to the different natural characteristics of optical and electrical devices.

Though ONNs come with higher parameter costs, they excel in terms of speed and energy efficiency, with the ability to operate at speeds of up to 100 GHz and consume as little as femtojoules per FLOP (floating point operation) [11]. This remarkable performance outpaces traditional electronic architectures, positioning ONNs as promising candidates for accelerating AI and machine learning tasks.

4. Conclusion

In conclusion, this article introduces an optical neural network based on MZI. The designed optical neural network is simulated at the physical level by utilizing the Neurophox framework. The activation function through this framework can be reconfigured by electrical bias, allowing a variety of nonlinear responses that have been programmed or trained. The experimental results show that the ONN has the expressive ability of a powerful photonic neural network, enabling them to excel in the machine learning task of MNIST's handwritten digital image classification dataset with high accuracy and fast convergence. The accuracy of training and testing data set is 98.6%

and 96.14%, respectively. We believe the simulation results show the great potential for ONN chip as an alternative hardware solution for the acceleration of deep neural network in the near future.

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