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Neural nonlinearity using a surface normal photodetector for diffractive optical neural networks

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Abstract: We propose a neural nonlinearity using a surface-normal photodetector with a response time of 5.7 μs and an energy efficiency of $<$ 10 nW/pixel. This device offers a significant improvement in free-space diffractive optical neural networks.

1. Introduction

Optical neural networks (ONNs) have gained significant interest recently for enabling high-speed processing at the speed of light while maintaining exceptional energy efficiency [1]. Consequently, various implementations of ONNs have been demonstrated ranging from bench-top setups [2,3] to integrated platforms that offer reduced size and improved energy efficiency [4]. Scaling integrated ONNs to handle more complex tasks with thousands or millions of neurons and multiple layers is hindered by challenges including photonic routing, larger propagation loss, and the need for intricate electronic circuitry to compensate for fabrication-induced errors, leading to lower energy efficiency and impractically large integrated systems. Free-space diffractive optical neural networks based on spatial light modulators, on the other hand, are proven to be a promising method to realize large scale network of neurons for image and video processing [2,3]. However, speed and energy efficiency of these networks are usually limited by the image sensor that is used to implement the nonlinear activation function [2,3]. Here, we propose a novel implementation of a nonlinear activation function in a diffractive ONN using a surface normal nonlinear photodetector (SNPD) that has previously been demonstrated as a high-speed electro-optic modulator [5]. Our proposed device can significantly improve the speed and energy efficiency in a diffractive ONN.

2. SNPD structure and characterization

2.1. Device structure

Figure 1(a) shows a sketch of the cross-section of the SNPD used in this work. It is composed of a multi-quantum-well (MQW) stack placed in the intrinsic region of a vertical p-i-n structure. The MQW is formed by 36 periods of $In_{0.52}Al_{0.48}As$ wells with 9 nm thickness and $In_{0.52}Al_{0.48}As$ barriers with 4 nm thickness, forming a total thickness of 468 nm. An asymmetric Fabry-Perot cavity is made by sandwiching the p-i-n structure between a

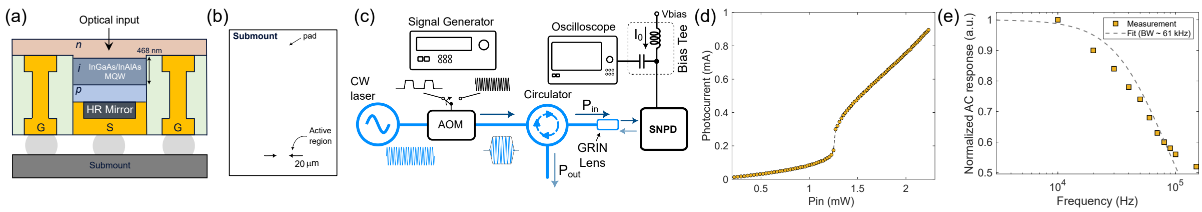

Fig. 1. (a) Sketch of the cross-section and (b) top-view photograph of the SNPD. (c) Experimental setup used to characterize the device. (d) The SNPD nonlinear response. The modulation signal is turned off in this case. (e) Frequency response of the SNPD measured at the wavelength of 1598 nm, while the AOM modulates the input optical signal.

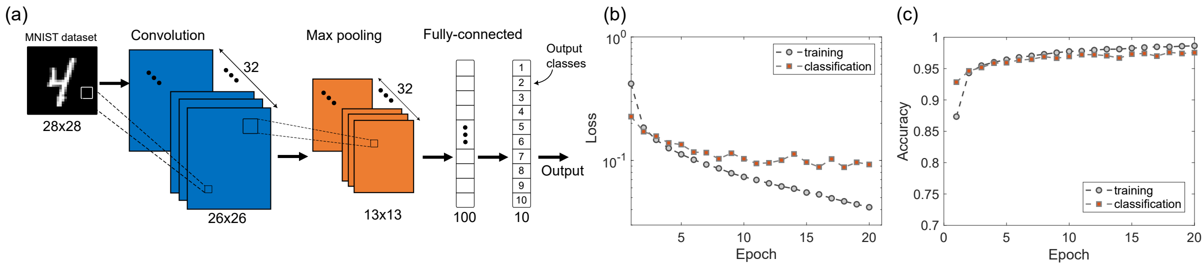

Fig. 2. MNIST data classification. (a) Architecture of the neural network. (b) Cross entropy loss and (c) classification accuracy as a function of number of epochs, for training and classification of the MNIST dataset.

highly reflective bottom mirror and a partially reflective top mirror. Figure 1(b) shows the microphotograph of the SNPD with an active diameter of 20μm.

2.2. *Device characterization*

Figure 1(c) shows the experimental setup to characterize the SNPD. To characterize the nonlinear behavior of the SNPD the optical power is swept at a fixed wavelength of 1598 nm. As shown in Fig. 1(d), once the optical power exceeds a threshold, i.e. 1.25 mW, the photocurrent increases at a much higher rate. To measure the response time of the device, an amplitude modulated light is coupled into the SNPD, operating in the nonlinear region, and the generated photocurrent was measured across a 50 Ω load. Figure 1(e) shows the normalized AC response of the SNPD (yellow squares) which suggests a 3-dB bandwidth of 61 kHz (equivalent to a rise time of about 5.7 μs). This is about three orders of magnitude faster than the typical millisecond response time of camera sensors. Note that the SNPD consumes about 10 nW/pixel which is three orders of magnitude more efficient than a typical camera.

3. Data classification using SNPD nonlinear response

To showcase the use of the SNPD nonlinear response in a neural network, the transfer function obtained from the measured data in Fig. 1(d) is used in the simulation platform, using Tensorflow libraries. This setup is utilized to classify MNIST datasets. Figure 2(a) shows the architecture of a simple neural network used in this work. The images are input to the convolution layer with 32 parallel 3×3 kernels with a stride of one and SNPD response as its activation function that replaces the standard ReLU function. A maxpooling layer down-samples the output of the convolution layer and is followed by a fully-connected layer with 100 neurons and SNPD nonlinear response. Finally, 10 neurons with softmax activation generate the classification results of the network. The input images are fed to the network with a batch size of 32. Figures 2(b) and 2(c) show the training and test cross-entropy loss and classification accuracy, respectively, both as a function of the number of epochs. Using the measured SNPD nonlinear response, the network achieves a test classification accuracy of about 97% that is the same as using an ideal ReLU in the same network.

4. Conclusion

We demonstrated the use of a surface-normal nonlinear photodetector in free-space diffractive ONNs as an alternative to commonly used camera sensors. The SNPD is three orders of magnitude faster and more efficient than a camera, and is independent to the state of polarization which makes it a promising candidate for use in a large scale free-space ONN setup.

References

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