Incoherent Fiber-based Optical Neuromorphic Computing Circuit

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Abstract: We present novel photonic neuromorphic computing scheme working with incoherent light while capable implementing negative weighting for the neural network and obtaining reliable/accurate computing of the linear multiply-accumulate function necessary for neural networks applications.

1. Introduction

Photonic computing holds the promise of achieving low-power and high-speed solutions to real-time machine learning and artificial intelligence applications, supporting future scalable and sustainable computing ecosystems which are expected to grow exponentially over the next decade. Most of the photonic computing solutions proposed to date rely on photonic integrated circuit (PIC) technology, silicon photonics chips (SIPH), or free-space optics [1–3], and use coherent interactions for the multiply-accumulate (MAC) operations [4–6].

These technologies encompass several issues including yield and scaling limitations due to large chip size, large accumulated loss over the numerous Mach-Zehnder Interferometers (MZI) included in most designs, the required tight phase control, and high sensitivity to local temperature or vibrations.

In contrast, fiber-optics and electro-optical communication industries offer a platitude of devices, which are larger in volume, but are based on mature technologies with high bandwidth and low power specifications alongside off-the-shelf availability and proven reliability.

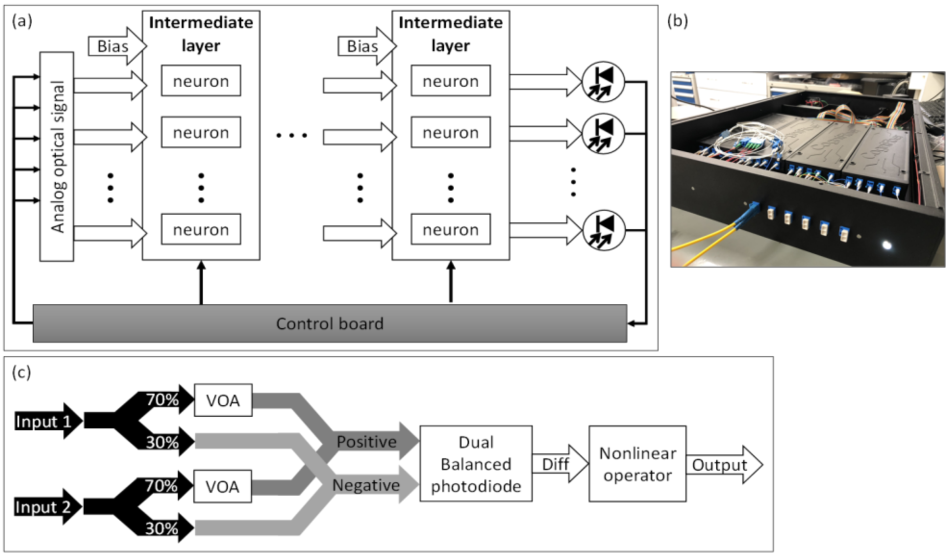

Figure 1: The constructed neuromorphic computing circuit. (a) system architecture; (b) picture of the assembled system; (c) schematic of the optical neuron. VOA – variable optical attenuator; Diff- differential output.

We have previously demonstrated an in-fiber-based optical computing unit, that combined with standard devices such as transceivers and Erbium-doped fiber amplifiers delivered both linear and non-linear functions required for neural network. While single unit results were impacted by coherence-induced phase-noise, a redundancy-assisted full network emulation (ResNet-18) demonstrated far-superior performance and accuracy over existing technologies [7,8].

While incoherent photonic computing systems were previously investigated, most of them do not solve the issue of negative weights which is required for scalable neural network computations. Past applications which address this issue [9,10] utilize SIPH techniques, with the aforementioned limitations.

In this paper, we present for the first time a fiber-based *incoherent photonic computing system*, which provides both negative and positive weights. We describe the system architecture, characterize neuron performance, and show numerical and experimental results of the processor.

2. Experimental setup

The complete photonic computing system architecture, comprised of multi-layer neural network, is depicted in Figure 1(a). Analog electronic signals are generated by the control board and are converted into analog optical signals using modulators. These signals are then weighted and injected into the first neural layer with addition of bias. Each neuron preforms an analog nonlinear function over the sum of weighted inputs and sends the resulting amplitude to the next layer. The outputs of the output layer neurons are read by the control board via photodiodes. Picture of the assembled system is seen in Figure 1(b). The operation of a single neuron with 2 inputs is illustrated schematically in Figure 1(c).

The neuron employs a push-pull mechanism in order to realize positive and negative weighting. Each input is split in a 30/70 ratio by a fiber-coupled splitter. The 70% leg, acting as the positive weight, passes through a variable optical attenuator (VOA) controlled individually by the control board. The 30% leg acts as the negative weight and is not attenuated. All the positive and negative weights legs are combined by a fiber-coupled combiner into a positive input port and negative input port and injected into a dual balanced photodiode. The differential output voltage is then converted into an analog optical signal which represents the total output of the neuron.

3. Results

We first characterized the timing of the positive and negative weights. For that purpose, a 20ns square pulse at 1500nm was inserted into a single input of the neuron. The output was measured by an oscilloscope (Keysight MXR604A), as shown in Figure 2(a). A delay line with length 40cm, equivalent to a 2ns delay, was then added to the optical path of the positive weights in order to show the negative and positive weights separately, as shown in Figure 2(b). The graph shows that the negative weights preceded the positive weights, and that the added spikes are indeed 2ns long, as expected.

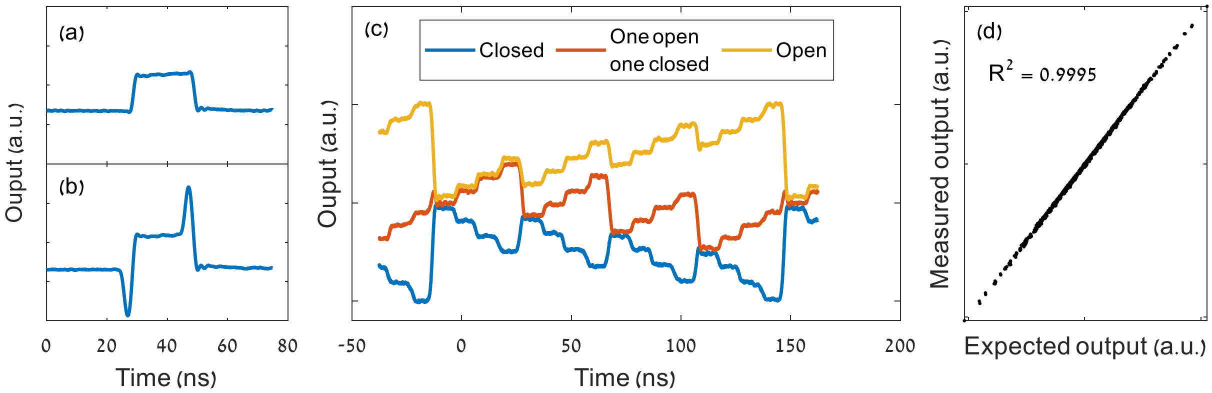

Figure 2: Experimental results. (a) 20ns pulse at 1550nm injected into a single neuron input; (b) the same pulse, with 40cm delay line (equivalent to 2ns) added to the positive optical path; (c) 4-level step input signal injected into 2 input ports: input1 with step period of 10ns and input 2 with step period of 40ns. The plot depicts the output when both VOAs are fully closed, fully open, and with one VOA closed and the other open; (d) Measured output vs. expected values.

We then inserted analog step functions with 4 levels into 2 inputs of the neuron, input1 with a 10ns step period and input2 with 40ns step period. The outputs were recorded at different states of the VOAs, shown in Figure 2(c). When both VOAs are closed the positive weight is equal to zero, resulting in negative descending steps. When both VOAs are fully open the intensity of the combined positive input is much higher than that of the combined negative input, leading to ascending steps. The state where one VOA is open and the other is closed is an intermediate state. The VOA of the shorter period input is open, so that input has a positive weight and hence displays ascending output. The VOA of the longer period input is closed, so it has a negative weighting and displays descending steps.

Table 1: CogniFiber Alpha prototype performance compared to competitors. Data is taken from Ref. [11].

	CogniFiber Alpha prototype	Nvidia DGX A100 (2021)	LightMatter Envise Server (2021)
Power (W)	300	6500	3000
Rate (K task/s)	100000	4800	24000
Efficiency (K task/(s*W))	333.3	0.73	8

We compared the output values measured by the dual balanced photodiode to the expected output values, as an assessment of the accuracy of the MAC operations, depicted in Figure 2(d). We expect the plot to be linear for an ideal MAC calculator. The plot in Figure 2(d) displays a linear fit with $R^2 = 0.9995$, implying an excellent MAC accuracy of the neuron!.

We completed a prototype comprising of 16 input channels and 4-layer classifier. The performance of CogniFiber's Alpha prototype system is given in Table 1, where the performance of other systems was estimated by multiplying 2-fold their published results for deep learning recommendation systems (DLMR), the simplest benchmark results available. We compare our results to Nvidia DGX A100, which is an industry standard, and to another photonic accelerator, LightMatter Envise server. Our results display an acceleration of up to 20 times that of competing systems, with 2 orders of magnitude increase in power efficiency.

The next evaluation included construction of a 3-layered neural network using our constructed processor. We have applied the realized photonic processor on "Seeds" dataset with 210 samples, 7 inputs, 3 classes. Good results were obtained as indicated in Figure 3 demonstrating both low loss as well as high accuracy in its performance.

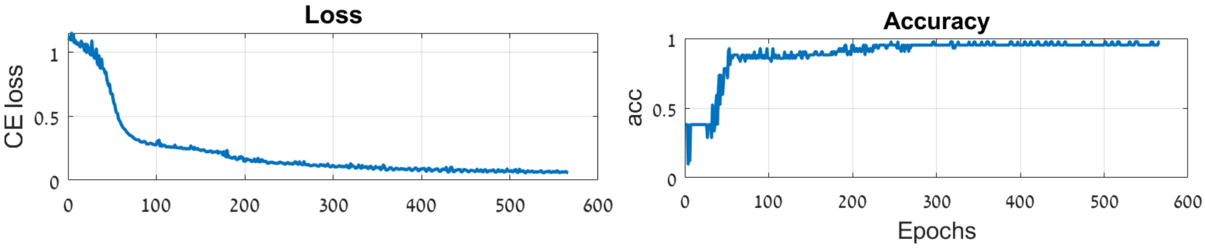

Figure 3: Experimental results. The obtained performance of loss and accuracy.

4. Conclusions

In conclusion, in this paper we have presented a photonic computing system based on hybrid fiber technology and optics communication devices, featuring positive and negative weighting scheme under incoherent data transmission conditions. We show that such design can achieve 5x to 20x acceleration while increasing power efficiency by over 100x. Demonstrating impressive performance having loss of <0.1 and accuracy of close to 1!.

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