Optical Implementation of Neural Learning Algorithms Based on Cross-gain Modulation in a Semiconductor Optical Amplifier

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ABSTRACT

Neuromorphic engineering has a wide range of applications in the fields of machine learning, pattern recognition, adaptive control, etc. Photonics, characterized by its high speed, wide bandwidth, low power consumption and massive parallelism, is an ideal way to realize ultrafast spiking neural networks (SNNs). Synaptic plasticity is believed to be critical for learning, memory and development in neural circuits. Experimental results have shown that changes of synapse are highly dependent on the relative timing of pre- and postsynaptic spikes. Synaptic plasticity in which presynaptic spikes preceding postsynaptic spikes results in strengthening, while the opposite timing results in weakening is called antisymmetric spike-timing-dependent plasticity (STDP) learning rule. And synaptic plasticity has the opposite effect under the same conditions is called antisymmetric anti-STDP learning rule. We proposed and experimentally demonstrated an optical implementation of neural learning algorithms, which can achieve both of antisymmetric STDP and anti-STDP learning rule, based on the cross-gain modulation (XGM) within a single semiconductor optical amplifier (SOA). The weight and height of the potentitation and depression window can be controlled by adjusting the injection current of the SOA, to mimic the biological antisymmetric STDP and anti-STDP learning rule more realistically. As the injection current increases, the width of depression and potentitation window decreases and height increases, due to the decreasing of recovery time and increasing of gain under a stronger injection current. Based on the demonstrated optical STDP circuit, ultrafast learning in optical SNNs can be realized.

Keywords: Spike-timing-dependent plasticity, Photonic Neural Network, Hebbian Learning Rule, Cross-gain Modulation, Neural network hardware, Optical signal processing, Optical computing.

1. INTRODUCTION

The spiking neural network (SNN), touted to be the third generation of neural network models, is a subtype of neural network which has become increasingly popular. Spiking neuron, as a basic computational unit of a SNN, is an excitable dynamical system to transfer information into spike trains [1, 2]. Compared with the previous generations of neural networks, i.e. the first generation, McCulloch-Pitts neuron-based neural network, and the second generation, Hopfield neural network, the SNN has practical advantages and can mimic the behavior of biological neurons more accurately [1]. There are two ways to implement SNNs. The first one is using simulators which is convenient and practical for exploring the quantitative behavior of neural networks [3]. However, it is limited in speed and also based on the von Neumann architecture, so it is not energy efficient. Another way is hardware emulation. Hardware emulation is an ideal way to implement SNNs, since it can operate in real-time, and the speed of the network is independent of the number of neurons or their coupling [3]. Recent progress has realized SNNs using modern very large scale integration (VLSI) circuits [3-6]. Though microelectronic neural networks are both fast and highly interconnected, there is a fundamental bandwidth bottleneck of microelectronic, keeping their speed limited. In contrast, since photonic has the advantages of high speed, wide bandwidth, low power consumption, and massive parallelism, photonic is ideal to implement SNNs, and a considerable number of photonic spiking neurons have been proposed in the recent five years [7-15]. Learning, the process of parameter adaption of a neural network to optimize the performance of a neural network for a given task, is crucial to neural circuits and makes it powerful, and the procedure for parameter adaption is called learning rule [16]. The weight ω_{ij} of a connection from neuron j to i is considered as a parameter, and the synapse of the neuron model is characterized by ω_{ij}. Synaptic plasticity provides the basis for learning and memory in neural circuits [17]. In 1949, Hebb

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made a famous assumption which is called Hebbian learning rule, and it can be precisely stated as follows: When an axon of cell A is near enough to excite cell B or repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased [18]. A large number of experimental results have shown that changes of synapse are highly dependent on the relative timing of pre- and postsynaptic spikes [19-22]. Spike-timing-dependent plasticity (STDP) is a form of Hebbian learning rule at the level of individual spikes, and various forms of STDP has been experimentally observed in biological systems [17, 23]. The changes of ω_{ij} are driven by precise timing between pre- and postsynaptic spikes. Recently, optical implementations of STDP have been proposed. In 2013, Fok etc. experimentally demonstrated an optical implementation of antisymmetric STDP for the first time based on cross-gain modulation (XGM) of a semiconductor optical amplifier (SOA) and cross-absorption modulation (XAM) of an electro-absorption modulators (EAM), and it allows independent control of the width and height of the potentiation and depression windows to implement different functions [24]. In 2015, Toole etc. implemented an optical antisymmetric STDP using the cooperative effects of XGM and nonlinear polarization rotation (NPR) within a single SOA, and they developed an STDP-based photonic approach towards the measurement of the angle of arrival (AOA) of a microwave signal [25]. In the same year, Ren etc. proposed an optical antisymmetric STDP scheme using two SOAs with weight-dependent learning window and reward modulation and they introduced a boundary mechanism for optical STDP synapses [26]; and Gholipour etc. proposed an optical STDP based on photodarkening phenomena in amorphous metal-sulphide microfibers to achieve four forms of STDP, including the antisymmetric STDP and anti-STDP learning rules, symmetric STDP and anti-STDP learning rules, and it operates at the wavelength of 532nm [14].

Here, we experimentally demonstrated an optical STDP circuit based on the XGM within a single SOA. Using the proposed optical STDP circuit, we can achieve antisymmetric STDP learning rule and antisymmetric anti-STDP learning rule. The different effects of positive and negative delays, where the postsynaptic spike follows the presynaptic spike and the postsynaptic spike precedes the presynaptic spike, respectively, are achieved by adjusting the injection current of the SOA. First, the STDP learning rule is reviewed in Section II. In Section III, the optical implementation of STDP learning rules is explored and experimentally developed.

2. STDP LEARNING RULE

A typical biological neuron is a multi-input and single-output system, including three functionally distinct parts, called dendrites, soma and axon [16], as shown in Fig. 1. Signals from other neurons are collected by dendrites, then transmitted to the soma; the soma is the nonlinear processing part of the neuron which plays the roles of temporally integrating and thresholding, and if the aggregated input spikes exceed the threshold, an output action potential is generated; the axon delivers the action potential to other neurons [16]. Two neurons are connected by a synapse, which is characterized by synapse weight ω_{ij}. Synaptic weight is not fixed but can change over time, and synaptic plasticity provides the basis for learning. Fig. 2(a) illustrates the basic schematics of synaptic learning in neurons. Synaptic plasticity in which presynaptic spikes preceding postsynaptic spikes results in strengthening, whereas the opposite timing results in weakening is called antisymmetric STDP learning rule, as shown in Fig. 2(b). And synaptic plasticity has the opposite effect under the same conditions is called antisymmetric anti-STDP learning rule, as shown in Fig. 2(c). The antisymmetric STDP learning function can be described as [27].

$$\Delta\omega = \begin{cases} a_+ \exp(-\Delta t / \tau_+), & if\,\Delta t > 0 \\ -a_- \exp(\Delta t / \tau_-), & if\,\Delta t < 0 \end{cases}. \tag{1}$$

The antisymmetric anti-STDP learning function can be described as [27]

$$\Delta\omega = \begin{cases} -a_- \exp(-\Delta t / \tau_-), & if\,\Delta t > 0 \\ a_+ \exp(\Delta t / \tau_+), & if\,\Delta t < 0 \end{cases}. \tag{2}$$

where $\Delta\omega$ is the relative change in synaptic strength, a and τ are the amplitude and time constant, respectively, and subscripts + and − identify the potentiation and depression window of the antisymmetric STDP and anti-STDP, $\Delta t = t_{post} - t_{pre}$ is the relative timing of pre- and postsynaptic spikes.

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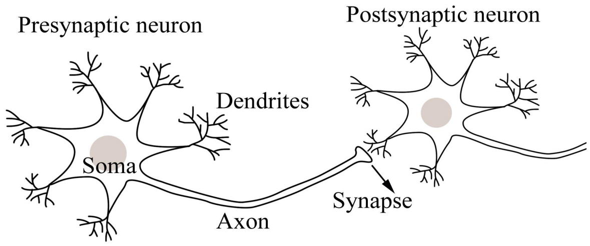

Fig.1 Schematic illustration of a typical biological neuron.

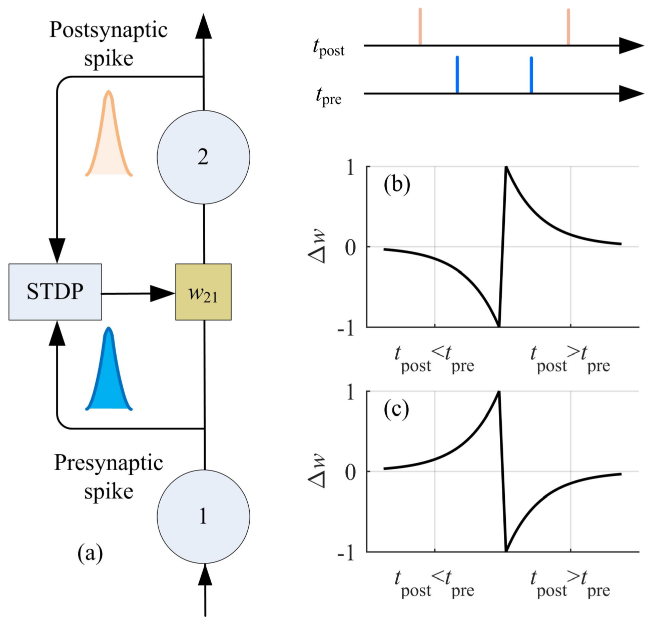

Fig.2 (a) Two neurons are connected with an optical synapse. ω_{21} is the strength weight between neuron 1 and 2. (b) (c) Biological antisymmetric STDP and anti-STDP curves, respectively. $\Delta\omega$ is the relative change in synaptic strength. t_{pre} and t_{post} are the precise timing of pre- and postsynaptic spikes.

3. OPTICAL STDP CIRCUIT

The experiment setups for optical spike trains generation and optical STDP circuit are shown in Fig. 3(i) and (ii), respectively. In Fig. 3(i), lights from two lasers at wavelength 1556.534nm (LD1, λ_{post}) and 1551.734nm (LD2, λ_{pre}) are multiplexed by a wavelength division multiplexer (WDM1), then they are modulated by a $LiNbO_3$ modulator driven by a pulse pattern generator (PPG). Therefore, the pre- and postsynaptic optical spike trains with the repetition rate of 622MHz and 80ps pulse width are generated. Furthermore, an erbium-doped fiber amplifier (EDFA) is used to amplify the pre- and postsynaptic spikes. To mimic a variable timing difference between the pre- and postsynaptic spikes, the spike trains are split into two branches by WDM2: the pre- and postsynaptic branch, and a 700ps variable optical delay line (VODL) is inserted into the postsynaptic branch.

In Fig. 3(ii), the optical STDP circuit is primarily composed of a single SOA (INPHENIX, IPSAD 1501C) and two WDMs (WDM3 and WDM4). The pre- and postsynaptic spikes are combined by WDM3 as inputs for the optical STDP circuit. The adjustment range of VODL is from -360ps to 340ps. When $\Delta t<0$, the leading postsynaptic spike is amplified without the influence of SOA's gain depletion, hence the output of CH1 (λ_{post}) is almost constant, as shown in the left side of Fig. 4(a). The lagging presynaptic spike experiences XGM due to the gain depletion in the SOA induced by the preceding spike, and the output of CH2 (λ_{pre}) decreases when $|\Delta t|$ decreases, as shown in the right side of Fig. 4(b). When $\Delta t>0$, the lagging postsynaptic spike experiences the gain depletion of SOA, and the output power increases when Δt increases, as shown in the right side of Fig. 4(a). The leading presynaptic spike experiences no XGM, so that CH2's

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output remains constant, as shown in the left side of Fig. 4(b). Through the linear addition and subtraction of CH1 and CH2 's output, antisymmetric STDP and anti-STDP curves can be achieved.

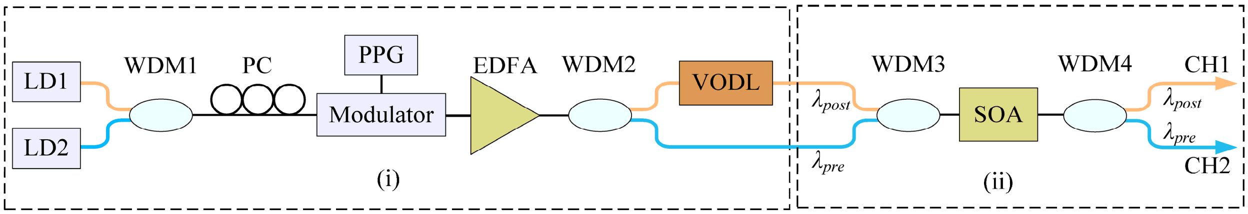

Fig. 3 The experiment setups for (i) the optical spike trains generation and (ii) optical STDP circuit. LD: laser diode; WDM: wavelength division multiplexer; PPG: pulse pattern generator; EDFA: erbium-doped fiber amplifier; VODL: variable optical delay line; PC: polarization controller.

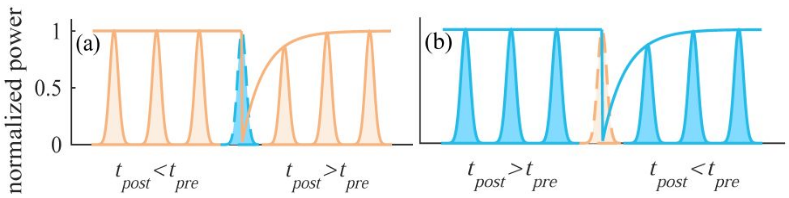

Fig 4. The mechanism for optical STDP circuit. The optical STDP circuit's output of (a) CH1, (b) CH2. The blue and orange spikes are the pre- and postsynaptic spikes, respectively. And the blue and orange lines indicate the output of CH1 and CH2, respectively.

In our experiment, the average powers of pre- and postsynaptic entering into the optical STDP circuit are both at -4.34dBm with the repetition rate of 622MHz and 80ps pulse-width. The experimentally measured STDP curves after normalization and linear addition and subtraction, using the proposed optical STDP circuit are shown in Fig.5. Fig. 5(a) is the antisymmetric STDP learning curves, and Fig. 5(b) is the antisymmetric anti-STDP learning curves. The different markers indicate the experimental data under the condition of different injection currents ranging from 210mA to 310mA, and the lines are the fitted curves using Eq. (2) and Eq. (3). The different effects of positive delay (Δt>0) and negative delays (Δt<0) can be achieved by adjusting the injection current of SOA. As the injection current increases, both the depression and potentitation windows' width decreases, and the height increases, due to the decreasing recovery time and increasing gain under a stronger injection current. The experimental measured STDP curves closely resemble the biological STDP curves [23].

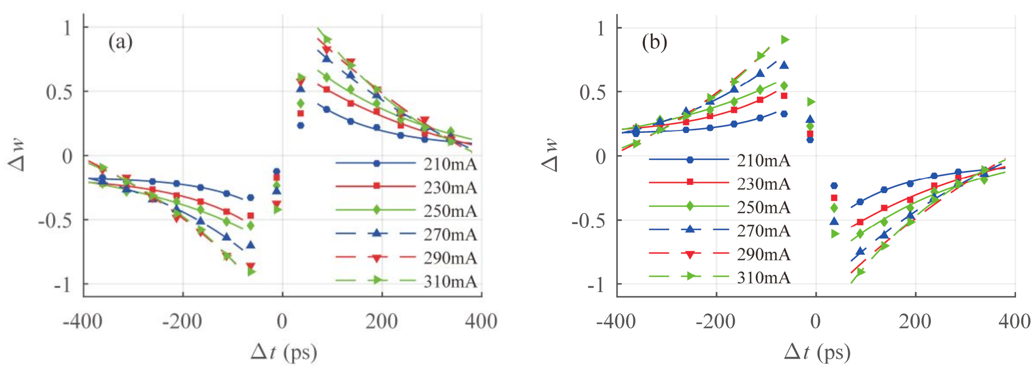

Fig. 5 Experimentally measured two forms of STDP curves with different injection currents. (a) Antisymmetric STDP curves, and (b) antisymmetric anti-STDP curves. The different markers indicate the experimental data and the lines are the fitted curves.

4. CONCLUSION

We have experimentally proposed an optical STDP circuit to mimic biological STDP characteristics. Using the proposed optical STDP circuit, antisymmetric STDP and anti-STDP curves can be achieved. The height and width of STDP

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windows can be adjusted by tuning the injection current of the SOA. The experimental measured STDP curves closely resemble the biological STDP curves, and the optical STDP circuit better mimics the behavior of biological STDP synapse. The demonstrated optical STDP circuit in this paper provides a new opportunity for realization of ultrafast learning in optical SNNs.

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