Photonic Implementation of Spike-Timing-Dependent Plasticity and Learning Algorithms of Biological Neural Systems

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(Top-Scoring Paper)

***Abstract*—The neurobiological learning algorithm, spike-timing-dependent plasticity (STDP), is demonstrated in a simple photonic system using the cooperative nonlinear effects of cross gain modulation and nonlinear polarization rotation, and supervised and unsupervised learning using photonic neuron principles are examined. An STDP-based supervised learning scheme is presented which is capable of mimicking a desirable spike pattern through learning and adaptation. Furthermore, unsupervised learning is illustrated by a principal component analysis system operating under similar learning rules. Finally, a photonic-distributed processing network capable of STDP-based unsupervised learning is theoretically explored.**

***Index Terms*—Feedback circuits, information theory, neural networks, nonlinear optics, optical signal processing.**

I. Introduction

NEUROMORPHIC engineering is an interdisciplinary field focused on mimicking neuro-biological architectures that takes advantage of the principles underlying biological neural networks in projects involved with adaptive control, learning, sensory processing, perception, and robotics. Researchers have made use of the leaky integrate and fire (LIF) model [1]–[3] proven as one of the most accurate neuron models, to investigate and mimic various neural algorithms, which provide an efficient and accurate means of performing complex tasks. The most interesting capabilities of the neuron are its abilities to both learn and adapt, which are cooperatively responsible for making biological neural systems so powerful. Synaptic weight plasticity is a fundamental element of adaptability, learning, and memory in neural systems, which allows for systems of neurons to adjust how they process information through the adjustment of the strength of synaptic connections between neurons in response to spiking activity. The most commonly cited process for describing learning in a biological neuron is the spike timing dependent plasticity (STDP) algorithm [4]–[7]. Functionally, STDP constitutes a mechanism for implementing a Hebbian learning rule in which strengths of connections between neurons are based on correlations between pre-synaptic and post-synaptic activity (i.e. "Neurons that fire together wire together").

Implementing neuromorphic algorithms solely with photonics enables high-capacity signal processing, ultrafast decision-making, and learning and adaptability at near-terahertz rates. Recently, a number of photonic-neuron circuits have been explored, including a LIF neuron [8]–[14], demonstration of a crayfish tail-flip escape response [15], and the STDP algorithm with potential applications [16]–[18]. Like those of its physiological counterpart, the functions performed by the photonic neuron are determined by the configuration of a set of parameters including the weights and delays of interconnections, the temporal integration time, and the spiking threshold.

This paper reviews the STDP algorithm and its applications with learning. We present our discovery of a photonic implementation of STDP experimentally and discuss its incorporation in both supervised learning and unsupervised learning applications. First, the STDP algorithm is described, and its photonic implementation is explored and experimentally developed in Section II. In Section III, the application of a photonic STDP module towards supervised learning is experimentally demonstrated. In Section IV, we expand the function of STDP to unsupervised learning, discussing the algorithm's role in principal component analysis (PCA), a technique for pattern recognition which relies on several key elements of photonic neurons.

II. The Neural Learning Algorithm—Spike Timing Dependent Plasticity (STDP)

The learning algorithm, STDP [4]–[7], is enacted in the synaptic connections between each neuron in a system, which allows for the adaptation exhibited by biological neural networks to complex environments despite a lack of a priori knowledge. As depicted by Fig. 1(a), the STDP algorithm describes the process by which the strength of the synaptic connection between two neurons is adjusted according to the relative timing of a

Manuscript received May 31, 2015; revised August 14, 2015; accepted August 24, 2015. Date of publication August 31, 2015; date of current version February 5, 2016. This work was supported by the National Science Foundation (ECCS 1342177, CMMI 1400100) and a grant from the University of Georgia Research Foundation, Inc.

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Digital Object Identifier 10.1109/JLT.2015.2475275

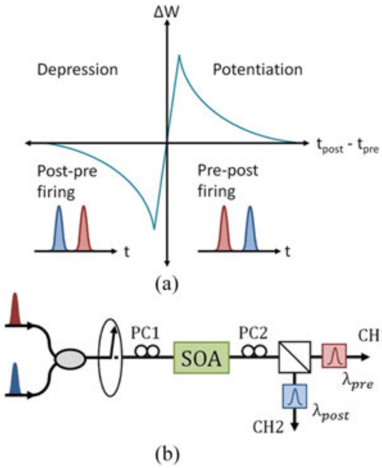

Fig. 1. (a) Illustration of the biological STDP characteristic. (b) Photonic STDP experimental setup.

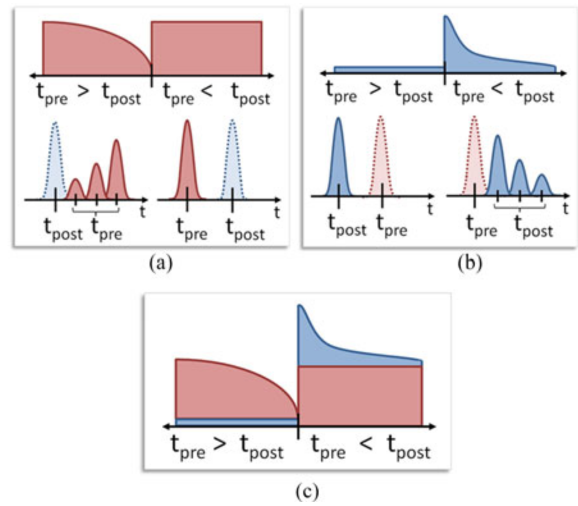

Fig. 2. (a) Channel 1 outputs. (b) Channel 2 outputs. (c) Linear combination of channels 1 and 2.

neuron's inputs (presynaptic spikes) and outputs (postsynaptic spikes). In one of the two STDP outcomes, the presynaptic spike received by a neuron contributes to the firing of a postsynaptic spike, resulting in a strengthening, or "potentiation," of a synaptic connection. Alternatively, "depression" occurs when a neuron fires prior to receiving input from another neuron, resulting in a weakening of the synaptic strength between the two. In this section, a photonic implementation of STDP characteristics, utilizing nonlinear polarization rotation (NPR) and cross gain modulation (XGM) within a single semiconductor optical amplifier (SOA), is designed and experimentally demonstrated [17], improving upon photonic STDP circuits requiring multiple electro-optic devices [16].

The relatively simple experimental setup for optical STDP, consisting primarily of one SOA, two bandpass filters, and a polarization beam splitter (PBS), is shown in Fig. 1(b). A polarizer and polarization controllers (PCs) are used for initial polarization alignment prior to operation. The pre- and post-synaptic spikes are at different wavelengths, which are generated through use of a fiber laser and four-wave mixing [17]. The pulse serving as the presynaptic spike is at 1550.12 nm ($\lambda_{\rm pre}$) with a repetition rate of 625 MHz (1600 ps period), solely for experimental purposes. With this lower repetition rate, the effects of the SOA's driving conditions on the STDP characteristic can be more fully explored, as it allows for a larger range of driving currents and consequent SOA recovery times to be studied. In actuality the repetition rate is limited by the recovery time of the SOA, which can be as low as 10 ps. The postsynaptic spike is of the same repetition rate and pulse width, but at 1551.62 nm. The pre- and postsynaptic spikes are combined using an optical coupler and launched into the photonic STDP circuit. The average powers of both pulse trains are set at -4 dBm, and the polarization states are aligned prior to the STDP circuit. Furthermore, a 600 ps tunable delay line is used in the presynaptic branch to mimic a variable timing difference between the pre- and postsynaptic spikes. To record the STDP characteristic, the delay is adjusted over its full range, from $\Delta t = t_{\rm post} - t_{\rm pre} = -300$ to 300 ps, the output power of both channels is recorded and combined at various delays, and the desired STDP characteristic is recognized.

To properly acquire the depression and potentiation window of the STDP curve, XGM, exemplified by channel 1, and NPR, exemplified by channel 2, are utilized. Fig. 2 illustrates the entire process, with Fig. 2(a) representing channel 1's output at $\lambda_{\rm pre}$, Fig. 2(b) representing channel 2's output at $\lambda_{\rm post}$, and Fig. 2(c) representing the linear combination of the two channels' power levels.

As shown by the left side of Fig. 2(a), a pulse entering the SOA depletes the device's gain, and the trailing pulse experiences minimal amplification. For more negative values of Δt, the SOA has more time to recover, and the trailing presynaptic spike experiences higher levels of amplification. If Δt is greater than zero, the leading presynaptic spike experiences the same maximum level of amplification across the range of positive Δt values, so no XGM results. As shown by the left side of Fig. 2(b), for all negative Δt values, the preceding postsynaptic spike experiences no NPR, so channel 2's output remains constant and minimal. For positive Δt values, however, the leading presynaptic spike induces additional birefringence in the SOA, causing the postsynaptic spike to experience NPR. Consequently, a portion of the postsynaptic spike passes through channel 2. As Δt increases, the level of NPR experienced by the trailing spike decreases, and the right side of Fig. 2(b) is formed. Fig. 2(c) represents the linearly combined power outputs of both channels for all values of Δt between -300 and 300 ps, outlining the desired STDP response.

The normalized STDP responses given by different SOA driving currents is shown in Fig. 3, which closely resemble the STDP response in biological neuron [7]. Similar to its biological counterpart, minor control of the potentiation and depression windows' height and width is achieved through adjustment of the SOA's driving current. As driving current increases, the SOA recovery time decreases, and the depletion curve decreases in width. Furthermore, higher driving current results in a stronger NPR effect due to the increased amplification and consequently increased induced birefringence; however, the width of the potentiation window remains relatively constant, likely as a result of competing effects. Higher driving currents result in a

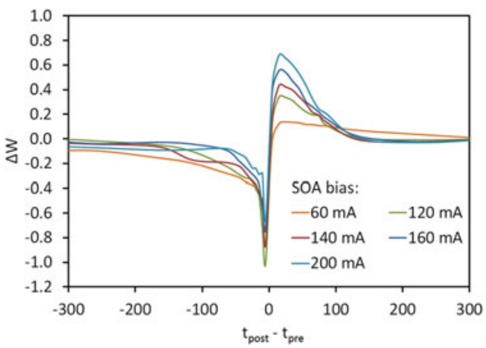

Fig. 3. Normalized photonic-based STDP characteristic.

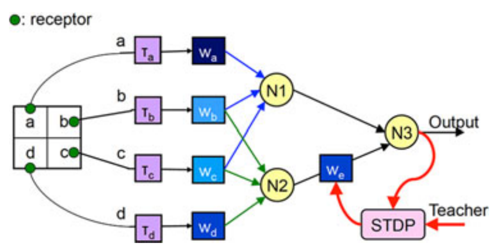

Fig. 4. Schematic illustration of supervised learning.

stronger NPR effect but also serve to restore the device's original birefringence more rapidly. The increasing NPR response and decreasing recovery time compete, and the potentiation window's width remains constant across all driving currents.

III. STDP for Supervised Learning

Learning based on experience is essential for a system to dynamically adapt to an unpredictable or changing environment, or one that is too complex to be characterized a priori. There are several different ways neurons can learn [19], and one such method, supervised learning, programs a system to perform a function defined in terms of its input-output pairs. Supervised learning relies on the use of a set of training pairs, where a sequence of training data is sent to the neuron's input and the corresponding desired output acts as the teacher. The neuron responds to the training input sequence, and the neuron response is compared with the teacher sequence. If the neuron response and teacher sequence are different, the synaptic strength between two neurons changes according to the STDP rule; otherwise, the synaptic strength is unchanged. After the learning phase, the teacher is removed, as the neuron is trained and ready to perform a specific task.

Using a photonic STDP circuit, we have demonstrated supervised learning in a photonic neuron in which a teacher determines the way that the photonic neuron should spike in response to its inputs [16]. Fig. 4 depicts a high-level schematic of supervised learning in photonic neurons. Both photonic neurons, N1 and N2, take several inputs (a-d) through receptors, which are weighted ($w_a - w_d$) and delayed ($\tau_a - \tau_d$) individually, and are temporally integrated at N1 and N2. An electro-optic modulator is used to convert the signal to optical spikes. Here, we are studying the synaptic plasticity between neuron N2 and N3

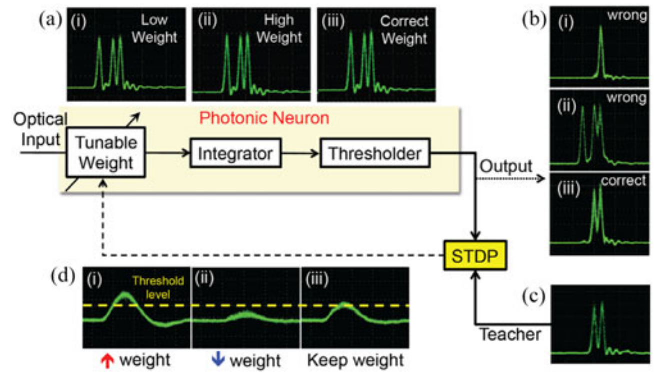

Fig. 5. Experimental results of automatic gain control in pulse-processing device (a photonic neuron) based on optical STDP. (a) Weighted output before integration at the photonic neuron. (b) Photonic neuron outputs. (c) Teacher signal. (d) Instruction signal from the STDP to indicate weight change. (i) Weight is too low. (ii) Weight is too high. (iii) Correct weight after learning.

by incorporating a photonic STDP circuit in the interconnection between N2 and N3. The initial weight w_e is at a random value, depending on the last operation of the photonic neuron, and is launched to the photonic neuron N3, which responds to the inputs depending on the current weight of the synaptic connection.

Since the initial weights are not optimized for detecting the desired signal, N3 is not spiking correctly in response to its inputs. Therefore, learning by means of the STDP circuit at the synaptic connection is desired. During the learning phase, N3's output, serving as a sequence of postsynaptic spikes, is compared with a teacher signal, serving as a sequence of presynaptic spikes, which represents the correct, desirable response to the neuron N3 inputs. If the photonic neuron is not spiking as the teacher is, the STDP circuit will send a signal, as illustrated by the red arrow in Fig. 4, indicating the necessary weight change to be applied to the synaptic connection. To enable a fast weight change response an electro-optic modulator is used as the variable weight device. The weight of each synaptic connection changes until the output matches what the teacher expects. After the learning phase is complete, the teacher is removed, and the photonic neuron still responds to its adjusted inputs in the desirable way as taught by the teacher.

Fig. 5 presents the experimental results of a supervised learning system. Fig. 5(a) depicts the weighted outputs before integration, 5(b) shows the photonic neuron outputs, 5(c) shows the teacher signal, and 5(d) illustrates the corresponding weight change needed as determined by the STDP circuit. Initially, in Fig. 5(a)i the interconnection strength is too weak, and the photonic neuron emits an undesirable output as shown in Fig. 5(b)i. According to the response at the photonic neuron output and the teacher [Fig. 5(c)], the STDP circuit will send a signal to indicate if an increase or decrease in weight is needed, as shown in Fig. 5(d). In the first case, an increase in weight is needed [Fig. 5(d)i]. On the other hand, if the weight is too weak [Fig. 5(a)ii], the photonic neuron will also have the wrong output, as shown in Fig. 5(b)ii. With the optical STDP enabled, the photonic neuron automatically adjusts the strength of the interconnection based on the result from the STDP circuit by

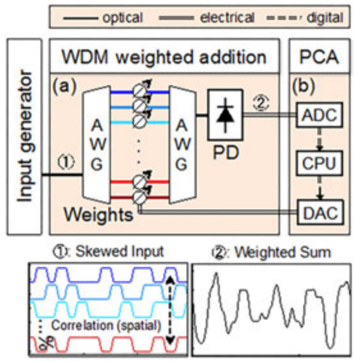

Fig. 6. Experimental setup of WDM weighted addition applied to PCA. (a) WDM weighted addition unit. (b) PCA algorithm, where ADC: analog-digital converter; CPU: central processor; DAC: digital-analog converter. Inset 1: Partially temporally and spatially correlated inputs. Insert 2: weighted sum of correlated channels.

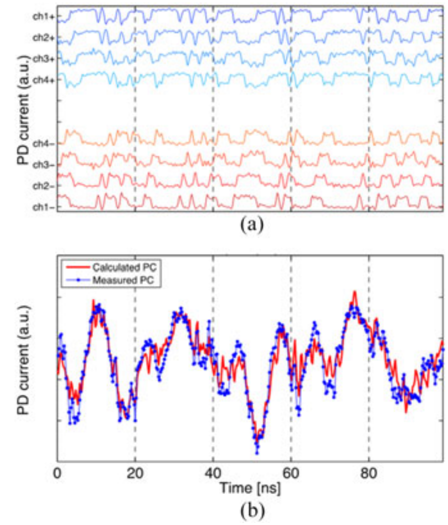

Fig. 7. Experimental results showing a 100 ns time window of a typical epoch. (a) A subset of partially correlated 4 positive input channels and their 4 negative complements on other wavelengths. (b) First principal component output as calculated by a software matrix decomposition-based PCA (red) compared to the measured output after convergence of the iterative algorithm (blue). Both calculated and measured PCA algorithms are applied to the measured inputs.

sending a signal [Fig. 5(d)] to adjust the weight. Fig. 5(a)iii and (b)iii show the photonic neuron output after it has learned from the teacher, indicating that the device has adjusted itself based on the STDP output and is spiking as expected by the teacher. After the learning phase the teacher is removed, and the processor continues to spike as the teacher instructed, as shown in Fig. 5(b)iii.

Photonic neurons are capable of processing information at billions of times a second, but a scalable learning scheme that allows such systems to adapt to a changing environment has yet to be well established. The development of the supervised learning capabilities presented here would enable a large range of new applications for photonics neurons, while taking advantage of the high bandwidths and processing speeds of photonics. Unlike prior approaches [15], our STDP learning system uses a single SOA, reducing the space occupied by a given STDP module. This increased scalability—especially if instantiated in an integrated platform—could enable complex learning operations, including principal component analysis (PCA) and independent component analysis (ICA).

IV. Principal Component Analysis with Optical STDP

The scalability of optical STDP would enable a number of useful algorithms. Here, we focus on a simple instantiation of principal component analysis (PCA) and describe how an STDP module can be implemented in such a system. principal component analysis (PCA) is a technique for unsupervised pattern recognition and dimensionality reduction of multidimensional random variables. In PCA the first principal component (PC) represents the original data in one dimension while maximizing the amount of "information explained."

To achieve PCA using a photonic neuron, a wavelength-division-multiplexing (WDM) weighted addition unit [20], [21] is developed. Weighted addition of an array of inputs is a fundamental component of neuron models. Microelectronic implementations of weighted addition suffer from interconnect limitations, which become more intractable as the dimension of the inputs increases. Digital electronic implementations, which use time-division multiplexing to accumulate summands, trade off bandwidth against fan-in (essentially the number of terms in the addition) [22]. By taking advantage of photonic bandwidths and by multiplexing many hundreds of signals onto a single waveguide, WDM is capable of removing that tradeoff and significantly improving interconnection performance. As explored in other works, WDM has enabled the experimental demonstration of weighted addition [23] with both wide bandwidth and scalable fan-in, and the experimental setup is illustrated in Fig. 6 [23]. In Fig. 6(a), the pair of array waveguide gratings (AWG) is used to separate the inputs and recombine them after weighting. The circles are variable optical attenuators, and their respected level of attenuation changes according to the PCA unit. A photodiode (PD) is used to convert the optical weighted signal back to the electrical domain. Inset (1) illustrates the partially temporally and spatially correlated inputs, and inset (2) shows the electrical output of the PD, which represents the weighted sum of correlated channels.

The proposed setup demonstrates for the first time a generalized Hebbian learning algorithm, implemented electronically, for synaptic modification, demonstrating that it converges iteratively to the first principal component of the inputs, as shown in Fig. 7. In this design, a CPU is responsible for computing correlations between postsynaptic and presynaptic signals, calculating the update rule, and controlling the weight bank, yielding a slow learning rate. The simple pair-wise operations required for the PCA controller described in the paper are feasible for a co-integrated microelectronic processor or other analog hardware, which could raise the learning rate to the hardware's bandwidth.

The Hebbian learning rule implemented in the described PCA system is known in the neuroscience field as activity-dependent synaptic plasticity (ADSP), introduced by Donald Hebb in

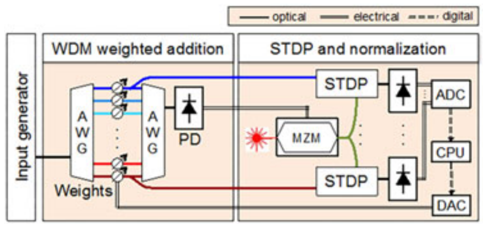

Fig. 8. Optoelectronic setup for scalable learning based on STDP. All-optical STDP circuits operating at the signal bandwidth enable Hebbian-type learning using only low-performance electronic hardware, which operates at the learning bandwidth ($<$ 10 MHz).

[24]. He suggested that synaptic connections should reinforce "when an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it." In our terminology, the axon of cell A represents one input (presynaptic) that is weighted and integrated by cell B, which in turn either releases or does not release an output spike (postsynaptic). This ADSP synaptic function, however, only assesses correlations between presynaptic and postsynaptic spike trains, rewarding positive correlations and penalizing negative correlations. Unfortunately, correlation does not imply causation. The STDP modification function, as described in Section II and implemented in Section III, extends ADSP, taking causation into account.

Neural models require independent tuning of their synaptic weights, which implies that each synaptic afferent requires an STDP module operating at a response time comparable to the picosecond timescales of inter-spike-intervals [25]. Since information is encoded in wavelength-carriers, these modules can be merged with the weighted addition optoelectronic circuit used for PCA and proposed in [23], as illustrated in Fig. 8. The output of the STDP function, which carries information of post/pre-synaptic synchrony, could be used by a lower module responsible for implementing a generalized Hebbian learning rule of the same sort as that used for PCA, shifting much of the processing to the optical domain. The latency of the weight controller (WC) loop defines the learning rate. Since the more complex nonlinear operation is already carried out by the STDP module, the controller's function is solely to translate a pulse to a weight update value. Like the PCA controller, the WC loop is feasible for current analog hardware technology.

Merging the weighted addition and STDP function is the next logical step towards a STDP-based learning rule for a photonic neuron. STDP-based learning, be it supervised or unsupervised, is exquisitely suited for pattern recognition. For example, a single LIF neuron equipped with STDP-learning is able to detect arbitrary spatiotemporal spike patterns, even when these patterns are embedded in equally dense noise spike trains [26]. A network of neurons with random interconnections and fixed delays can self-organize via STDP-learning into polychronous groups [27]. The number of co-existing polychronous groups that can be stored in the network far exceeds the number of nodes. For a spiking neural network with fixed connection delays, the product of learning—memory—is stored entirely in the synaptic weights, which in our case can be electronically recorded. Pattern recognition at near-terahertz speeds significantly expands the current technology's bandwidth capabilities for RF signal processing, allowing for applications such as RF fingerprinting and cognitive radio [28]–[30].

V. Summary

We have experimentally demonstrated an optical STDP module, a key algorithm for spike-based learning in spiking neural networks [4]–[7]. Unlike prior approaches, the functionality of STDP is collapsed into a single device, allowing for greater scalability in practical systems. We also describe an instantiation of optoelectronic PCA, and propose how the optical STDP module can be utilized to perform this algorithm. Together, these approaches pave the way for a scalable, adaptable photonic processing system.

Biological neural networks possess unique advantages over traditional computers, including power efficiency, computational efficiency for holistic tasks, and adaptability to new environments. Distilling some biological properties for signal processing has already proven extremely interesting and greatly beneficial towards advancing current signal processing technologies. Mimicking a key neural learning algorithm in photonics—spike timing dependent plasticity (STDP)—would enable ultrafast learning capabilities in photonics. Systems of neurons and STDP modules could adapt at unprecedented speeds and bandwidths to incoming signals, providing applications in spaces such as cognitive radio, RF fingerprinting, spectral hole exploitation, and ultrafast prediction.

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Prof. Prucnal was the Technical Chair and General Chair of the IEEE Topical Meeting on Photonics in Switching in 1997 and 1999, respectively. He is a Fellow of the Optical Society of America. Hereceived the Rudolf Kingslake Medal from the SPIE, cited for his seminal paper on photonic switching, the Gold Medal from the Faculty of Physics, Mathematics and Optics from Comenius University in Slovakia, in 2006, for his contributions to research in photonics. the Princeton Engineering Council Awards for Excellence in Teaching in 2004, 2006, and 2008, the University Graduate Mentoring Award in 2006, and the Walter Curtis Johnson Prize for Teaching Excellence in electrical engineering, as well as the Distinguished Teacher Award from Princeton's School of Engineering and Applied Science, in 2009.

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Dr. Fok received the 2014 Ralph E. Powe Junior Faculty Enhancement Award from ORAU, the University of Georgia College of Engineering Award for Excellence in Research Faculty Award in 2015. When she was a graduate student, she has received the IEEE Photonics Society 2010 Graduate Student Fellowship, Special Merit in 2008 Hong Kong Institution of Science Young Scientist Awards, First Prize in 2007 IEEE Hong Kong Section Postgraduate Student Paper Contest, the 2006 Optical Society of America Incubic/Milton Chang Student Travel Grant Award, the 2005 IEEE Lasers and Electro-Optics Society Graduate Student Fellowship Award, and the 2005 Thomas HC Cheung Postgraduate Scholarship in Science and Engineering from the Hong Kong Association of University Women.