A DFB-LD-based photonic neuromorphic network for spatiotemporal pattern recognition

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Abstract: We present a photonic neuromorphic network using DFB-LDs for spatiotemporal pattern recognition. Complete input patterns are investigated theoretically and experimentally. The output peak powers decrease with the difference between the target pattern and other patterns.

1. Introduction

In recent years, the demand for high-speed and efficient information processing has triggered a rising interest in neuromorphic photonics [1-3]. Relying on ultrafast pulse generation, low energy dissipation, and dynamics with biological plausibility, neuromorphic photonics has great potential to be applied in different scenarios, such as realizing a parallel neuromorphic computing framework [4] or a novel brain-inspired system for specific tasks [5]. As the fashion of information interaction in spiking neural network, spatiotemporal patterns are ubiquitous in various sections including coding, processing, and decoding. Through the introduction of the time variable, spatiotemporal patterns enrich the complexity of information expression at a superb energy efficiency, giving rise to perplexities for recognition. Therefore, the fast, accurate, and target-adjustable spatiotemporal pattern recognition is indispensable for neuromorphic photonics.

In both the electrical and optical domains, there have been some studies about pattern recognition [6,7]. In [6], spatiotemporal pattern recognition is demonstrated through resistive switching synapses at a magnitude of ~ms (near to the biological counterpart). More recently, an all-optical phase-change-material-based (PCM) network is presented and the performance on pattern recognition is evaluated [7]. Due to the limitation placed by the switching of PCM, the network is capable of spatial-only pattern recognition with a capacity of 2^N (e.g. patterns like "1100", N stands for the number of input branches). Here, we propose a photonic neuromorphic network based on distributed-feedback-laser-diodes (DFB-LDs), which emulates the dynamics of biological membrane potential for spatiotemporal pattern recognition.

2. Principle of the network

In Fig. 1, the DFB-LD-based photonic neuromorphic network consists of an input layer with N DFB-LDs, a weighted addition module, an output layer with a single DFB-LD, and a spike-timing-dependent-plasticity (STDP) module. The upper schematic shows the processing of the input pattern. At first, an input pattern includes N spike-timing-varying spikes separately located at N input branches. It is assumed that every spike occupies one of the N

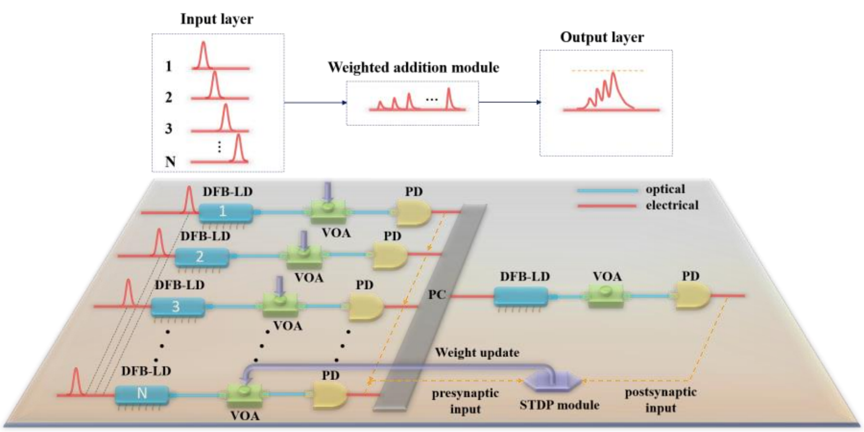

Fig. 1. Schematic of the DFB-LD-based photonic neuromorphic network, including an input layer, a weighted addition module, an output layer, and a STDP module for weight update. DFB-LD: distributed-feedback-laser-diode. VOA: variable optical attenuator. PD: photodetector. PC: power combiner. STDP: spike-timing-dependent-plasticity.

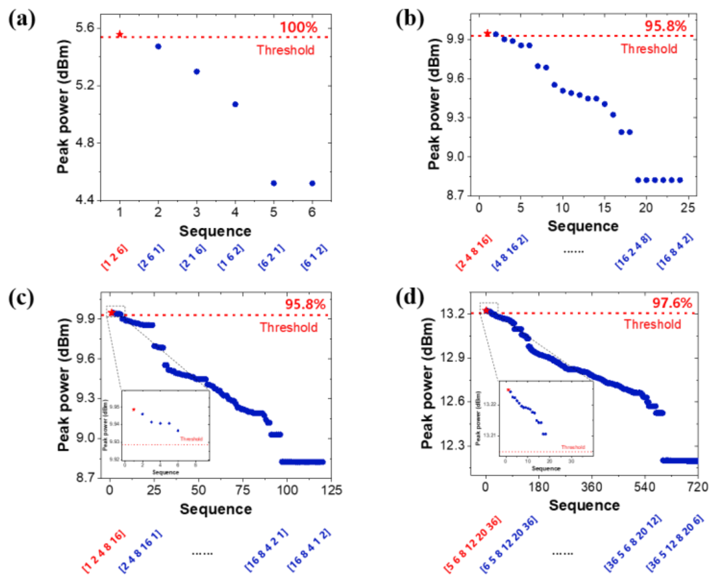

Fig. 2. Simulation results of peak powers induced by different input patterns. The cases that N=3, 4, 5, and 6 correspond to (a), (b), (c), and (d), respectively.

time steps for simplicity. The DFB-LDs reshape the spikes into exponentially-decaying shapes (denoted as V_{ed}). Then, the weight is given by variable optical attenuators (VOAs), followed by the O/E conversion in photodetectors (PDs) and the power combiner (PC) for the weighted V_{ed}. Finally, the membrane-potential-like dynamics is generated in the DFB-LD of output layer (denoted as V_{mem}). It reaches peak value only when the weight distribution is positively correlated with the spike timings (e.g. $w_1<w_2<w_3$ for target pattern "1 2 3"), thus realizing the spatiotemporal pattern recognition.

Note that the spectrum width of the spikes should slightly exceed the direct-modulation bandwidth of DFB-LDs for the generation of V_{ed} and V_{mem}, hence the time scale of the network is determined. V_{mem} reflects the temporal interaction among the spikes in various input patterns. Through the rate equation of DFB-LD [8], we simulate the peak powers of V_{mem} for all A_N^N input patterns. In the case, the spike is Gaussian-like with a width (full-width-at-half-maximum, FWHM) of 10 ps and the time step is 50 ps. As is shown in Fig. 2, the target patterns contribute to the highest peak powers in all cases (N=3, 4, 5, and 6 for (a), (b), (c), and (d), respectively). At the same time, the peak powers decrease with the difference between the target pattern (red) and other patterns (blue). Below the x-axis, there are indicators of weight distribution and input patterns. In fact, the discrimination of threshold is determined by the signal-to-noise ratio of the link. Here we consider a typical 0.02 dB loss resolution of a commercial VOA and set the threshold regardless of any noise. The recognition accuracy is estimated at a condition of uniform possibility for each input pattern and marked in the Fig. 2. Accordingly, the ability to recognize spatiotemporal patterns of the proposed network is verified.

3. Experimental results and discussion

Experimental setup, results, and a learning scheme via a STDP module for the network are presented by Fig. 3. In Fig. 3(a), three DFB-LDs (Emcore-Ortel, 1751A-35-BB-FC-10), VOAs, balanced-PDs (fsphotonics, FS-PD-B-2030), and a power combiner (Mini-Circuits, ZFRSC-123+) are used to investigate the network at N=2. In addition, input patterns are generated by an arbitrary waveform generator (AWG, Keysight M8195A). Besides, an oscilloscope (Keysight, DSO-S 804A) monitors the output. Note that the DFB-LDs are driven by laser diode controllers (Thorlabs, lTC4001) with an external modulation bandwidth of 150 kHz. Figures 3(b) and 3(c) indicate the results of two input patterns with a peak amplitude of 206 mV for the target pattern "1 2" and 160 mV for another pattern "2 1". The spike width is 1 μs and the time step is 2 μs for N=2. Performed by Fig. 3(d), for the cases N=3 and 4, we consider the weighted-addition results as the input to test the DFB-LD in the output layer. Figures 3(e) and 3(f) indicate that the peak amplitude is 204 mV and 149 mV for input pattern "1 2 3 4" and "4 3 2 1", respectively. It is noteworthy that the pump trace is monitored by the R6 port on the rear panel of the laser diode controller. The spike width is 1 μs and 0.5 μs corresponding to N=3 and N=4 with a time step of 2.5 μs and 1.3 μs, respectively. Ultimately, the complete input patterns are shown in Figs. 3(g) (N=3) and 3(h) (N=4). It can be

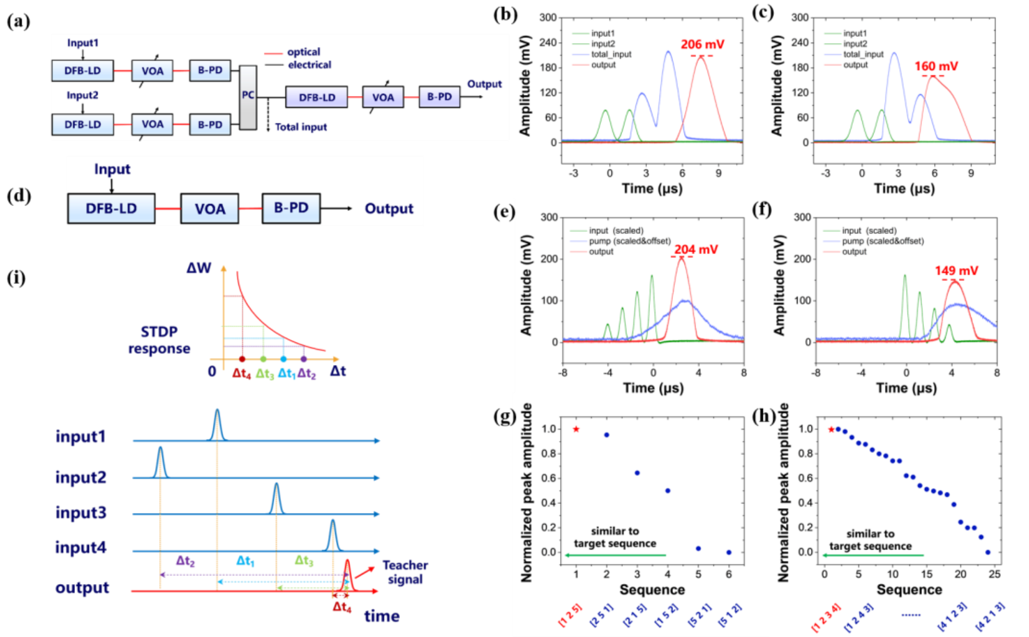

Fig. 3. Experimental setup and results for the proposed network, as well as the schematic of learning target pattern with a STDP module. (a) Experimental setup when N=2. (b, c) Results for input patterns of “1 2”and “2 1”. (d) Experimental setup when N=3 and 4. (e, f) Results for input patterns of “1 2 3 4” and “4 3 2 1”. (g, h) Results for complete input patterns when N=3 and 4. (i) A STDP-assisted learning scheme. DFB-LD: distributed-feedback-laser-diode. VOA: variable optical attenuator. B-PD: balanced-photodetector. PC: power combiner. STDP: spike-timing-dependent-plasticity.

observed that the trends match well with the simulation results in Fig. 2, which demonstrates the validity of the network for spatiotemporal pattern recognition.

In Fig. 3(i), we present the learning ability for arbitrary target pattern recognition through the STDP module in Fig. 1, which is feasible for all A_N^N input patterns. As an example of target pattern “2 1 3 4”, a teacher signal as the postsynaptic input (marked in Fig. 1) is sent to the STDP module following the final time step. By the time-difference-dependent potentiation of STDP, the weights can be updated in an unsupervised manner. Consequently, the positive correlation between spike timings and weights is achieved and the network has learnt a new target pattern for recognition.

4. Conclusion and future work

A DFB-LD-based photonic neuromorphic network is theoretically and experimentally demonstrated for A_N^N spatiotemporal patterns recognition. Besides, a STDP-assisted unsupervised learning scheme of arbitrary target pattern for the network is performed. Future work includes the improvement of recognition accuracy by optimization of weights, the analysis about spike widths and time steps corresponding to various modulation bandwidths of the DFB-LD, and the demonstration of STDP-assisted unsupervised learning ability of the network.

5. Acknowledgment

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