# Micro-Ring-Resonator Based Passive Photonic Spike-Time-Dependent-Plasticity Scheme for Unsupervised Learning in Optical Neural Networks

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Abstract: In this work, a photonic spike-time-dependent-plasticity scheme based on high-order passive ring resonators is demonstrated. Numerical simulations confirmed the validity of the approach assuming post and pre-synaptic quantum dot laser neurons. © 2020 The Author(s)

## 1. Introduction

The last years a tremendous effort has been invested in transferring bio-inspired neural structures to the photonic domain, so as to realize optical counterparts to biological cognitive circuits [1]. In this context, photonic machine learning primitives such as deep neural networks and reservoir computing have emerged, providing a different set of merits [2]. On the other hand, neural training, which is of paramount importance for the efficient implementation of such schemes, still heavily relies on algorithms that are executed by conventional electronic circuits. Exceptions to this processing bottleneck, are recent works that aims toward implementing Hebbian learning strategies such as time-spike-dependent-plasticity (STDP) directly in the photonic domain [3, 4]. In these approaches, two semiconductor optical amplifiers (SOA) are used so as to sense post and pre synaptic spike's time of arrival through the variation of the SOA's gain, similar to a pump-probe approach. A key requirement for this scheme is that the synaptic neurons should be tuned to emit at different wavelengths, so as to be resolved by integrated optical filters. In this work, we demonstrate an alternative photonic STDP approach that relies on the use of high-order, micro-ring resonators (MRR). In our case, inter-spike timing is assessed by monitoring the power difference at the MRR's output, induced by intra-cavity effects such as Kerr effect and two photon absorption (TPA). The proposed scheme is passive thus has marginal power consumption. The ability to use multiple inputs (clockwise and counter clockwise fields), eliminates the requirement of neurons to emit at different wavelengths, thus can boost scalability. Furthermore, by adjusting the relaxation time of free carriers at the MRR a tunable potentiation/depression window can be generated so as to tackle tasks with different time-constants.



Fig.1 a) generic STDP scheme where each laser neuron (LN) feed its output to the STDP module. The STDP module generate a control signal that can electro-optically tune the synapse's strength e.g. through a variable optical attenuator (VOA). b: the proposed passive STDP module

## 2. Principle of Operation

The generic concept of an optical two-neuron synaptic system is depicted in Fig.1a; two laser neurons (LN) are connected through a synapse, which's strength is regulated by the STDP module. In detail, the output of the pre-synaptic neuron is split into two parts by a waveguide splitter (WS) with an asymmetric ratio (e.g. 1/99), where "a" corresponds to the weak signal (probe) and "b" to the main signal (pump). These signals feed the STDP module,

whereas the "b" signal is routed after the STDP to the post synaptic neuron as signal "c". A similar operation is designated for the post synaptic neuron. The "a" and "b" signals are used similar to a pump-probe setup, whereas the "c" is fed to subsequent neurons. Fig.1b depicts the internal architecture for the proposed photonic STDP. Our scheme consists of two similar MRRs, the first receives two discrete inputs; a weak signal (type "a") and strong (type "b") from the pre synaptic and post synaptic neuron respectively. The second's MRR has reverse inputs (fig.1b). Neural signals are encoded as optical gaussian spikes with variable peak power (1mW for pump-spikes and 10µWatt for the probe-spikes), spike duration is set to 100ps (Fig.2a) and their center frequency coinciding with the MRR's resonance.

The principle of operation can be summarized as follows: when a strong pre-synaptic spike propagates, eg. clockwise, in the first MRR, it causes a significant increase in the population of free-carriers due to TPA. At the same time, the elevated peak power and the resonant nature of the MRR, allow a frequency shift in the transfer function due to Kerreffect. These non-linear changes, directly affect the weak spike (post-synaptic) that propagates in the other direction, eg. counter-clockwise and exits the MRR through the drop port. Therefore, if the pre-synaptic neuron fires earlier than the post-synaptic, but within a time-frame governed by the relaxation time of free-carriers, transmission ( $\tau_{free}=100$ ps) at the drop port of the MRR changes (Fig.2b). A symmetric transmission is acquired if we utilize a strong post-synaptic with a weak pre-synaptic in the second MRR (Fig.2c). Therefore, if two photodiodes track the transmission of both MRRs and their response is subtracted, the typical STDP transfer function is acquired (Fig.2d). These results are obtained, through a travelling-wave approach [5] that assumes ring radius of 50µm, intra-cavity losses of  $\alpha=4.4$ dB/cm, symmetric coupling coefficient of  $\kappa=0.2$ . It is clear that an advantageous STDP response would provide a large onoff ratio (between depressed and enhanced regimes). The simulations indicated that the power difference at the drop port varies with  $\kappa$  and is maximized at  $\kappa=0.2$ . Furthermore, for constant coupling, the drop port variation follows a monotonic reduction with losses, whereas the same applies when increasing the MRR's circumference.



Fig.2 a: Typical time trace for the weak pre-synaptic and post synaptic spikes, b: transmission for the drop port of the first single order MRR (see fig.1), c: transmission of the second single order MRR. d: combined of both MRRS transmission ( $\Delta P_1$ - $\Delta P_2$ ). e: typical schematic of the second order STDP, f: combined transmission for a single order and second order STDP scheme.

This behavior can be linked to the reduction of the intra-cavity power that in turn diminishes the MRR's nonlinear response. Therefore, for the specific application, the MRR is driven to an optimum operational point, when the drop response exhibits enhanced  $\frac{dP}{df}$ , which means that minor resonance's shifts are translated to significant power variations. Moreover, the bandwidth of the drop port's transfer function should be larger than the bandwidth of the neural spike. These two demands can be simultaneously met if high-order MRRs are considered; offering a box-like response with increased bandwidth [6]. In fig.2e we present a variation of the MRR based STDP based on secondorder MRRs. In this approach the pre and post synaptic signals are inserted through the in and drop port respectively. We computed the STDP response assuming the same linear losses and ring radius and varying the circular-straight waveguide coupling coefficient  $\kappa_1$  (fig.2e) while we set circular-circular coupling coefficient at its optimal input  $\kappa_r$ . r=0.044 so as to have single peak at the drop port [6]. We identified that for the losses-ring radii assumed, optimum condition was met when  $\kappa_1$ =0.35; the STDP response is plotted in Fig.2f alongside the single MRR's transmission. It can be seen that the on-off ratio is enhanced by a factor of 6dB. A critical parameter for the STDP scheme is the power requirements; although our approach is fully passive, it still demands an optical spike with adequate peak power so as to trigger TPA and Kerr effect. In Fig.3a the variation at the drop port is plotted versus the peak power of the presynaptic spike for a noiseless system. It can be seen that for an optimized second order MRR, even a moderate peak power of 1mW can offer a 15dB power variation. On the other hand, the existence of noise in the STDP scheme is

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anticipated to decrease the system's efficiency by affecting the recorded on-off ratio. In order to investigate the impact of noise, we have assumed that neural spikes are pre-amplified by an erbium doped optical amplifier (EDFA) prior to MRR injection. The optical power at the output of the EDFA is constant. Therefore, if higher gain is used, it will result to optical spikes with the same peak power but with reduced signal to noise ratio. In Fig.3b it can be seen that the increase of gain (aka noise) will result to an exponential decrease of  $\Delta P$ , which is equal to the maximum on-off ratio of the STDP function. Finally, in order to validate the suitability of our approach with photonic neural networks, we have devised an application scenario that utilizes 13 pre synaptic photonic neurons realized as single section quantumdot lasers [7]. Each pre-synaptic neuron independently feeds a single post synaptic neuron. The peak power of a single pre-synaptic spike cannot excite the post-synaptic neuron and only the cumulative firing can lead to post synaptic firing (Fig.3c). Therefore, seven neurons are biased to generate spikes at a fixed time frame, whereas the time of firing, of the other neurons is random. The time difference between the post-synaptic and each pre-synaptic spike is computed and the above MRR STDP function of Fig.2d is applied following the learning formula:  $W_i = f_{sat}(W_i + R_I \cdot f(\Delta t_i))$ , where  $R_L=0.05$  is the learning rate,  $\Delta t_i$  is the time difference between the spikes,  $W_i$  is the computed weight  $\in [0,1]$ , f is the MRR's STDP function and  $f_{sat}$  is saturation function aiming to provide an upper bound for the weights. In order to provide a data set for the unsupervised learning process the above process was repeated 100 times. In Fig.3d the weights for two synapses is computed versus the number of iterations. The first weight corresponds to a presynaptic neuron that fire at a predefined time, therefore tends to be responsible for the post-synaptic firing, while the second is a neuron that fires randomly. It is evident that with any supervision during training the randomly firing neuron's synaptic weight converges to zero, while the fixed firing neuron is enhanced and set to 1.



Fig.3 a)  $\Delta P$ : on-off ratio of the STDP function versus the peak power of the pre-synaptic spike. b)  $\Delta P$  versus the gain of a hypothetical EDFA prior to the STDP module that is reverse proportional to the SNR of the signal c) time trace of the post-synaptic neuron, orange arrow marks the accumulation of (integrate & fire) pre-synaptic spikes, whereas with a red arrow we mark the post-synaptic firing. d) MRR-STDP weights for two neurons versus the iterations of the unsupervised learning process.

## 3. Conclusion

In this work, we demonstrated numerical results concerning a micro-ring based passive STDP scheme. The principle of operation was validated and the role of critical device's parameters was highlighted. The proposed scheme can provide unsupervised learning capabilities for optical neural networks with marginal power consumption, scalability and robust operation. A demonstration of the MRR-STDP was performed employing multiple quantum-dot spiking neurons, confirming the proposed scheme's suitability for practical applications.

#### Acknowledgments

This project has received funding from the EU H2020 NEOTERIC project (871330) and the Hellenic Foundation for Research and Innovation (HFRI) and the General Secretariat for Research and Technology (GSRT), under grant agreement No 2247 (NEBULA project)

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