Reservoir Computing with Nonlinear Micro-Resonators on a Silicon Photonics Chip

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Abstract – We present here recent advances in the use of a small network of nonlinear micro-resonators integrated on a Silicon chip as a reservoir computer. We provide numerical evidence that this novel photonic integrated circuit can perform binary-type tasks (e.g.: the XOR task or multi-bit header recognition task) at bitrate of 20 Gb/s with a performance level adequate for telecom applications. We analyze the impact of key operational parameters (e.g.: optical power injected) and topological properties of the network on the level of performance of the proposed architecture. Finally, we will compare the performance between this new chip with a previous generation of passive reservoir [1] realized with splitters and combiners without any internal nonlinearity.

Introduction – In the last five years, there has been a reboot of neuro-inspired optical computing via the transposition of a simple, yet very efficient machine learning paradigm known as reservoir computing [2,3]. The proposed architectures rely on typical photonic architectures such as electro-optic oscillators [4,5], semiconductor laser diodes [6], or semi-conductor amplifiers [7]. Although the level of performance of these architectures reaches up to 1 million pattern recognitions per second [8] and an energy efficiency increased by two orders of magnitude [6], these setups still suffer from a lack of integration.

The emergence of integrated photonics has attracted a lot attention in recent years with the promise of developing novel functionalities not exceeding a few square centimeters on a chip.

In this proceeding, we report on the performance of a small network (4x4 nodes) of nonlinear micro-resonators on a silicon chip as candidate architecture for reservoir computing. We show there exist regimes of operation where the dynamical network outperforms a purely passive reservoir structure comprised of splitters and combiners [1]. This opens a new venue for the use of novel classes of photonic integrated circuits for neuro-inspired computing.

1. Theoretical Framework

1.1 Model for the nonlinear micro-ring resonator

The dynamical system under consideration is a non-linear micro-ring resonator, illustrated in Fig. 1(a). This system is described within the framework of coupled mode theory (CMT) by the following mathematical model [9]:

$$\frac{da}{dt} = \left[j(\omega_r - \omega + \delta\omega_{nl}) - \frac{\gamma_{loss}}{2}\right] a + \kappa s_{in}\,, \quad (1)$$

$$\frac{d\Delta T}{dt} = -\frac{\Delta T}{\tau_{ph}} + \frac{\Gamma_{th}\gamma_{abs}|a|^2}{\rho_{Si} c_{p,Si} V_{th}}\,, \quad (2)$$

$$\frac{dN}{dt} = -\frac{N}{\tau_{fc}} + \frac{\Gamma_{FCA}\beta_{Si} c^2 |a|^4}{2\hbar\omega V_{FCA}^2 n_g^2}\,, \quad (3)$$

where a denotes the complex mode amplitude, ΔT the temperature variations and N the free carrier concentration; ω is the frequency of the input optical carrier and ω_r the resonance frequency of the micro-ring, $\delta\omega_{nl}(\Delta T, N)$ is the nonlinear frequency detuning, $\gamma_{loss}(|a|^2, N)$ is the total loss in the cavity due to imperfect coupling, radiation and absorption.

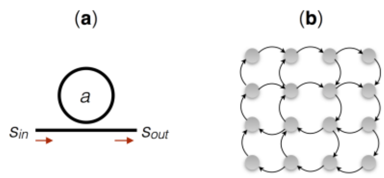

Figure 1 – (a) Illustration of a micro-ring coupled to a waveguide with input (s_{in}) and output (s_{out}) signals and cavity mode (a). There is a simple mathematical relationship between the three quantities: $s_{out} = e^{i\phi}s_{in} + \kappa a$ with ϕ a coupling phase. (b) SWIRL topology of a 4x4 network. Each gray circle represents a micro-ring.

The coefficient κ is the coupling coefficient between the ring and the waveguide as shown in Fig. 1(a) and s_{in} is the input optical signal. The remaining parameters are associated with material properties: τ_{ph} and τ_{fc} are the relaxation times for the temperature and the free carriers, respectively. β_{Si} is the constant governing the two-photon absorption. $c_{p,Si}$ is the thermal capacity; ρ_{Si} is the density of silicon; n_g is the group index equal in first approximation to the index of bulk silicon. $V_{th,FCA}$ and $\Gamma_{th,FCA}$ are the effective volumes and confinement factor for thermal and free-carrier absorption effects, respectively. Their numerical values are identical to those used in Ref. [9].

1.2 Network structure

We consider in our study the so-called SWIRL topology shown in Fig. 1(b). It allows for the presence of recurrent loops in the network necessary for solving tasks requiring memory (such as multi-step time-series forecasting) [4-6]. This topology has been already used for passive reservoir computer architectures [1].

1.3 Reservoir computing based on network of nonlinear micro-resonators

In the reservoir computing approach [2,3], the structure of the network is not trained to solve a given task, only the weights of a linear combination $\hat{y}_{RC}$ of the network's states (*readout layer*) are trained to reproduce a target output y_{target} based on a given set of inputs.

In our simulations, we consider that input signal is sent to every node in the network. The output signal is realized as the weighted sum of the optical intensity of each node sampled at discrete times $\Delta t = 6.25\ ps$.

The nodes are trained using ridge regression and five-fold cross-validation on sets of 10,000 bits used in the XOR task. The XOR task is a nonlinear problem consisting of estimating from the k-th bit $x[k]$, the quantity $y[k]$ defined by the following expression:

$$y[k] = x[k] \oplus x[k-1]. \qquad (4)$$

We analyze the performance of our reservoir computing architecture in terms of bit error rate (BER).

2. Simulations results

In this section, we perform a comparative performance analysis of 4x4 SWIRL networks with (i) passive components similar to that of Ref. [1] and (ii) with nonlinear micro-rings.

We first study the influence of the size of a network of nonlinear micro-rings on the XOR-task performance at two different bit rates 10 Gb/s and 20 Gb/s. Figure 2(a) shows the level of performance for these various networks. Similar to an all-passive reservoir, the performance scales with the size of the reservoir. However, we observe consistently a lower BER at 20 Gb/s. This dependence of performance on the data rate is linked to the presence of intrinsic time-scales of dynamics in the micro-ring that do not exist in purely passive reservoir. A bitrate of 20 Gb/s corresponds based on extensive simulations to an optimum operational point to use a reservoir with nonlinear micro-rings.

In Fig. 2(b), we compare the performance on the XOR task of a reservoir with passive elements and another one with nonlinear rings. They operate under similar conditions in terms of number of nodes (4x4: 16 nodes), data rate (20 Gb/s), and injected optical power (0.5 mW per node).

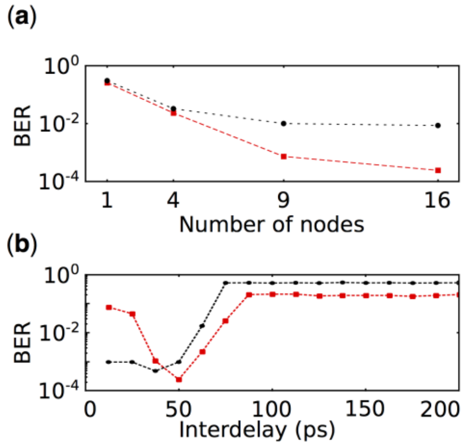

Figure 2 – (a) BER on the XOR task for a *n*x*n* reservoir with n=1,2,3,4 at two different bit rates: 10 Gb/s (black curve) and 20 Gb/s (red curve). (b) Comparative performance in terms of BER for a 4x4 passive reservoir (black curve) and reservoir composed of nonlinear micro-ring (red curve) at 20 Gb/s.

We analyze how the interdelay (the propagation delay between the nodes) in the reservoir relative to the bit rate influences the performance level (this test has been also realized in Ref. [1]). In these conditions, we notice that the minimum BER is smaller than the one obtained by a fully passive reservoir. We also observe that for an interdelay greater than 50 ps, the reservoir based on micro-rings systematically performs better than its passive counterpart.

3. Conclusion

We have demonstrated in this proceeding preliminary results on the level of performance of a small network of nonlinear micro-rings integrated on a photonic chip for reservoir computing applications. The addition of nonlinear components allows us to perform better on the nonlinear XOR task in similar operating conditions. This motivates further investigation to fully characterize the performance of this type of architecture and opens new venues toward all-optical signal processing.

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