Towards high-performance spatially parallel optical reservoir computing

J. Pauwels,[1,2] G. Van der Sande,[2] A. Bouwens,[3,4] M. Haelterman,[4] and S. Massar[1]

[1] Université libre de Bruxelles, LIQ, avenue F.D. Roosevelt 50, 1050 Brussels, Belgium
[2] Vrije Universiteit Brussel, APHY, Pleinlaan 2, 1050 Brussels, Belgium
[3] KU Leuven, Molecular Imaging and Photonics, Celestijnenlaan 200F, 3000 Leuven, Belgium
[4] Université libre de Bruxelles, OPERA, avenue F.D. Roosevelt 50, 1050 Brussels, Belgium

We present numerical results on a spatially parallel photonic reservoir computer. This reservoir is based on a linear free-space Fabry-Pérot cavity with a nonlinear readout of the optical field. The back-end coupler of the cavity is replaced with a diffractive optical element to couple the neurons that are located in the spatial extent of the cavity input coupler. We discuss the effect of the diffractive coupling scheme on the simulated reservoir computing performance on a standard benchmark test.

Introduction to optical reservoir computing

On a daily basis, we all benefit from the fruitful combination of digital encoding and microelectronic integration based on the Von Neumann architecture. This successful computing scheme is not easily challenged when it comes to heavy calculation-based procedures. However, tasks such as speech and facial recognition are computationally very demanding and thus require large, costly and energy consuming computer resources. Yet our brain, which works very differently, solves these tasks in the blink of an eye. This observation explains the renewed interest in neuron-inspired or neuromorphic computation. At the same time, due to a strong demand for high capacity optical communication links, photonic manufacturing is thriving. The marriage of these two fields has reinvigorated the field of photonic based computing.

Our research targets efficient (high speed and low power) analogue photonic computing systems based on the neuron inspired algorithm known as reservoir computing (RC) [1-3]. This computing paradigm offers a framework to exploit the transient dynamics of a recurrent nonlinear dynamical system for performing useful computations. The simplifying feature that makes reservoir computers easy to train is that only the output weights are trained, see Fig. 1 for a schematic. Over the past few years, several photonic reservoir computers have been reported [4-8]. In this paper, we report on a system that uses a linear optical reservoir, with nonlinearity implemented in the output layer by the readout photodiodes, following [7,8], but built so as to exploit the massive parallelism and high bandwidth available in the optical domain. As such, our work will allow us to overcome the limited scalability and parallelism of previous photonic reservoir computers.

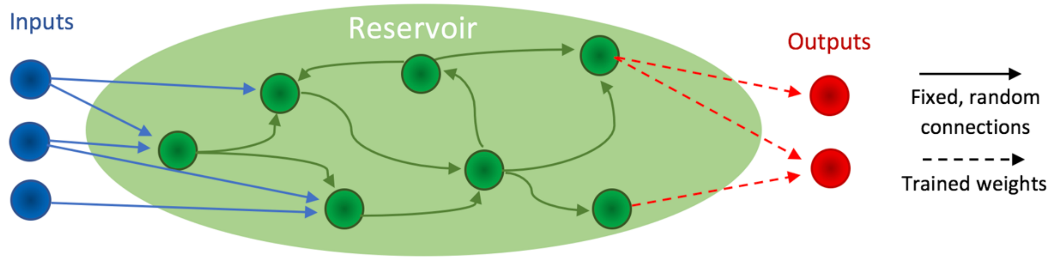

Figure 1. Reservoir computing scheme with random, fixed internal connections and trained readout weights.

Spatially parallel optical reservoir computer

In this work, the reservoir consists of a linear free-space Fabry-Pérot cavity with quadratic readout of the optical field. The neurons are encoded as a 2-dimensional grid of spots on the transverse spatial extent of the input coupler. A lens inside the cavity, with its Fourier planes on the front- and backend couplers, transforms these spots into collimated beams which hit the same position on the backend coupler under a discrete set of angles. At this cavity backend, a reflective diffractive optical element (DOE) with a periodic profile diffracts each incident beam into multiple reflected beams under the same discrete set of angles. These beams are then again imaged onto the grid of neuron spots on the input coupler by the intracavity lens. This way, the DOE effectively couples the neurons with variable connection strengths, depending on its exact profile. The injected signal is an intensity modulated Gaussian beam which we focus onto the input coupler. This means that data is injected into the central neuron on the input coupler.

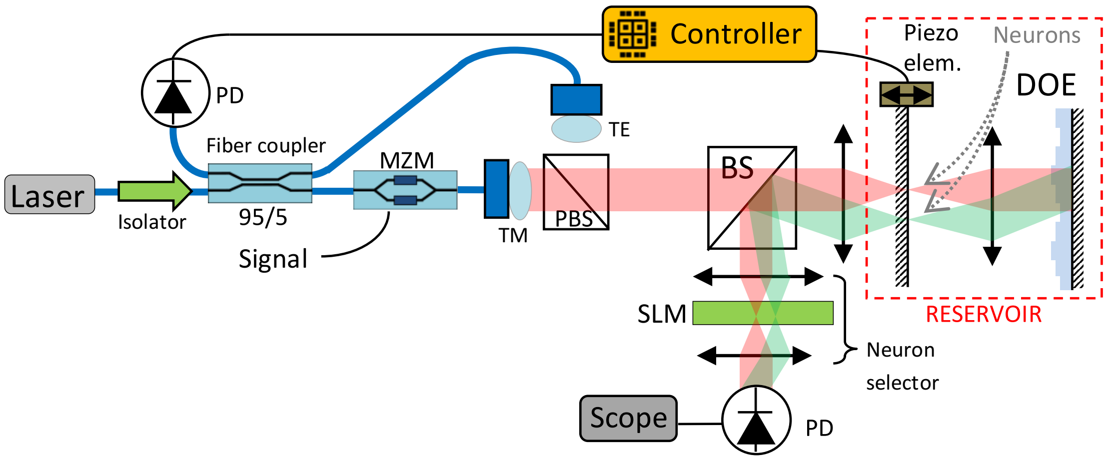

Figure 2. Schematic of spatially parallel optical reservoir computing setup based on a linear Fabry-Pérot cavity and quadratic readout of the optical field. The reservoir itself consists of an input coupler (whose position is stabilized by a Piezoelectric element), a lens, and a diffractive optical element (DOE). Other optical elements are a Mach Zehnder Modulator (MZM) to encode the input signal, a Polarizing Beam Splitter (PBS), a Beam Splitter (BS), a Spatial Light Modulator (SLM) to encode the output weights, Photodiodes (PD). The TM mode carries the signal and the TE mode is used to stabilize the cavity resonance.

Diffractive coupling scheme: degree of symmetry

As the DOE is implemented using a phase-only spatial light modulator (SLM) of 1920 by 1080 pixels we can programmatically change the coupling strengths between the neurons in the reservoir. The discrete neuron positions impose 2-dimensional periodicity on the phase profile (see Fig. 3) and the SLM imposes a pixelated phase profile. Hence, we construct the phase profile by tiling identical patches of 56 by 56 pixels, which still leaves us with many degrees of freedom. The main aim of the present work was to investigate numerically what was the best phase pattern to put on these patches. To limit the amount of variables in the optimization procedure of the DOE phase, the phase profiles in these simulations were constructed using a small set of 30 periodic base functions. We constructed profiles with varying degrees of symmetry: 4-fold symmetry, 2-fold symmetry and no symmetry. Naturally the resulting coupling strengths between neurons, with examples visualized in Fig. 4, show the same symmetries. When evaluating the RC performance, we iteratively optimize these profiles. And in this optimization the profiles with 2-fold symmetry and those without symmetry can evolve towards a 4-fold symmetric profile, up to the point where they become visually indistinguishable from a true 4-fold symmetric profile. However, since per construction these profiles are not perfectly 4-fold symmetric, we will refer to them as quasi 4-fold symmetric.

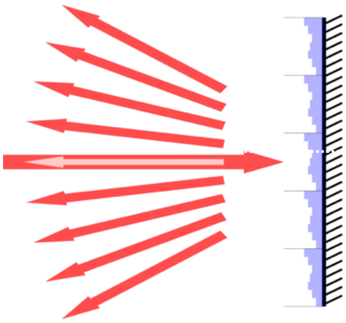

Fig. 3. The DOE's periodic phase profile ensures diffraction under a discrete set of angles.

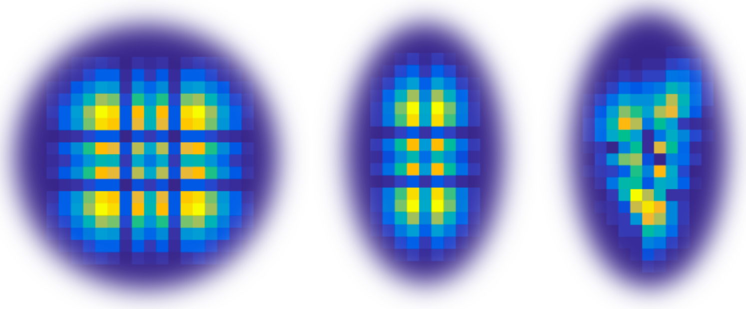

Fig. 4. Visualizations of how the DOE couples a neuron (at the center) to other neurons. Yellow means strong coupling, dark blue means no coupling. Coupling schemes are shown with 4-fold, 2-fold and no symmetry. Quasi 4-fold symmetric coupling schemes are visually indistinguishable from schemes with true 4-fold symmetry.

Results

We numerically investigated the effect of the diffractive coupling scheme and its symmetry on the simulated RC performance on the NARMA 10 task (a standard benchmark test, described e.g. in [4,8]). In Fig. 5 the signal reconstruction error on this task (lower is better) is plotted in function the average readout signal to noise ratio (SNR) for various degrees of symmetry in the DOE phase profile. Each marker corresponds with a phase profile optimized using the simulated annealing method.

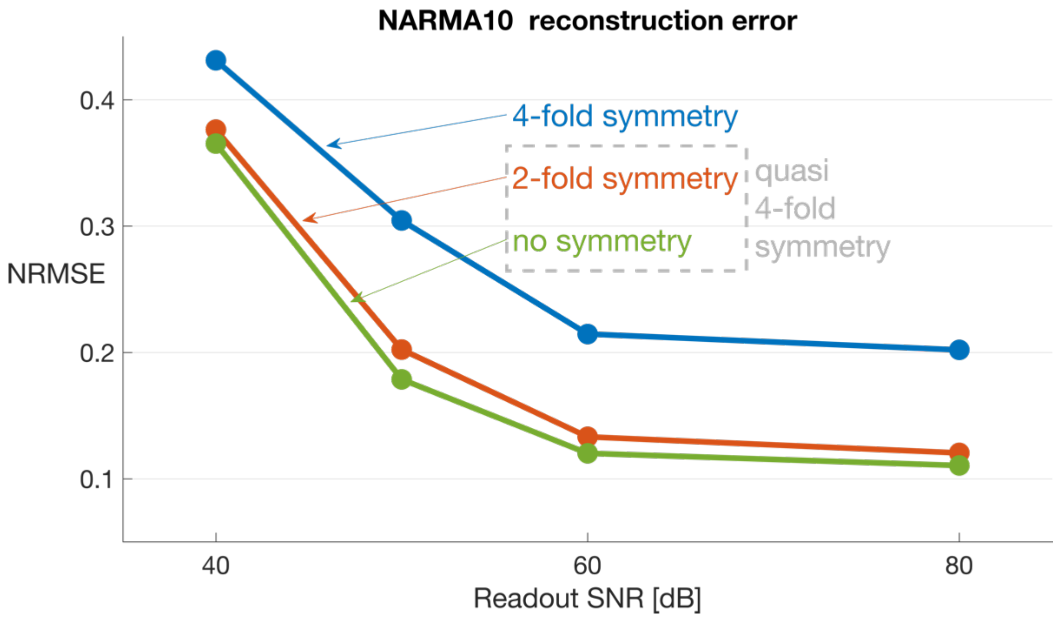

Fig. 5. Simulated RC performance on NARMA10 signal reconstruction task for varying degrees of symmetry of the diffractive coupling scheme, after optimization using simulated annealing. Noise on the output photodiode was simulated and the readout SNRs were calculated w.r.t. the average neural power level. For perfect reconstruction, the Normalized Root Mean Square Error (NRMSE) is 0.

These results clearly indicate that perfect symmetry should be avoided. Perfect symmetry causes redundancy in the neural responses and thereby decreases the effective number of neurons in the reservoir. The total number of neurons is currently 81. With perfect 2-fold symmetry, the reconstruction error shows a slight increase compared with the non-symmetric phase profiles, because the number of distinct neural responses is effectively halved. With perfect 4-fold symmetry, the reconstruction error grows even more significantly as this number is halved again. However, we observed that symmetric or quasi-symmetric coupling schemes result in more homogeneous distribution of optical power among neurons. This effect significantly increases the SNRs of the peripheral neurons.
Combining these considerations, we learn that quasi 4-fold symmetric phase profiles maximize the number of distinct neural responses with adequate readout SNR. The small deviations from perfect symmetry ensure complete variability in the neuron states without destroying the homogeneity of the power distribution over the neurons, thus maintaining an acceptable SNR for each neuron.

Conclusion

In this works we carried out numerical simulations of a photonic implementation of reservoir computing with neurons encoded in a parallel and scalable scheme. We have learned that quasi-symmetric phase profiles optimize RC performance on the benchmark task that was presented. This knowledge will allow us to speed up the optimization of the phase profile when the experiment is built.

References

[1] H. Jaeger, and H. Haas, "Harnessing nonlinearity: predicting chaotic systems and saving energy in wireless communication," Science 304, 78, 2004

[2] W. Maass, T. Natschläger, and H. Markram, "Real-time computing without stable states: a new framework for neural computation based on perturbations," Neural Comp. 14, 2531, 2002

[3] D. Verstraeten, B. Schrauwen, M. D'Haene, and D. Stroobandt, "An experimental unification of reservoir computing methods," Neural Networks 20, 391, 2007

[4] Y. Paquot, F. Duport, A. Smerieri, J. Dambre, B. Schrauwen, M. Haelterman, and S. Massar, "Optoelectronic reservoir computing," Sci. Rep. 2, 287, 2012

[5] L. Larger, M.C. Soriano, D. Brunner, L. Appeltant, J.M. Gutierrez, L. Pesquera, C.R. Mirasso, and I. Fischer, "Photonic information processing beyond Turing: An optoelectronic implementation of reservoir computing," Opt. Exp. 20, 3241, 2012

[6] D. Brunner, M.C. Soriano, C.R. Mirasso, and I. Fischer, "Parallel photonic information processing at gigabyte per second data rates using transient states," Nature Commun. 4, 1364, 2013

[7] K. Vandoorne, P. Mechet, T. Van Vaerenbergh, M. Fiers, G. Morthier, D. Verstraeten, B. Schrauwen, J. Dambre, and P. Bienstman, "Experimental demonstration of reservoir computing on a silicon photonics chip," Nat. Commun. 5, 3541, 2014

[8] Q. Vinckier, F. Duport, A. Smerieri, K. Vandoorne, P. Bienstman, M. Haelterman, and S. Massar, "High-performance photonic reservoir computer based on a coherently driven passive cavity," Optica, 2(5), 438-446, 2015