Improving Performance of Analogue Readout Layers for Photonic Reservoir Computers with Online Learning

Piotr Antonik,[1†] **Marc Haelterman,**[2] **Serge Massar**[1]
[1] Laboratoire d'Information Quantique, Université libre de Bruxelles,
Avenue F. D. Roosevelt 50, CP 224, Brussels, Belgium
[2] Service OPERA-Photonique, Université libre de Bruxelles,
Avenue F. D. Roosevelt 50, CP 194/5, Brussels, Belgium
[†] Email: pantonik@ulb.ac.be, Phone: +32 (0)2 650 4486

Reservoir Computing is a bio-inspired computing paradigm for processing time-dependent signals (Jaeger and Haas 2004; Maass, Natschläger, and Markram 2002). The performance of its hardware implementation (see e.g. (Soriano et al. 2015) for a review) is comparable to state-of-the-art digital algorithms on a series of benchmark tasks. The major bottleneck of these implementation is the readout layer, based on slow offline post-processing. Several analogue solutions have been proposed (Smerieri et al. 2012; Duport et al. 2016; Vinckier et al. 2016), but all suffered from noticeable decrease in performance due to added complexity of the setup. Here we propose the online learning approach to solve these issues. We present an experimental reservoir computer with a simple analogue readout layer, based on previous works, and show numerically that online learning allows to disregard the added complexity of an analogue layer and obtain the same level of performance as with a digital layer. This work thus demonstrates that online training allows building high-performance fully-analogue reservoir computers, and represents an important step towards experimental validation of the proposed solution.

Theory and methods

Reservoir computing. A general reservoir computer is described in (Lukoševičius and Jaeger 2009). In our implementation we use a sine transfer function and a ring topology to simplify the interconnection matrix, so that only the first neighbour nodes are connected (Paquot et al. 2012). The system is trained online, using the simple gradient descent algorithm, as in (Antonik et al. 2016a).

Benchmark tasks. We tested the performance of our system on two benchmark tasks, commonly used by the RC community: wireless channel equalisation and NARMA10. The first, introduced in (Jaeger and Haas 2004) aims at recovering the transmitted message from the output of a noisy nonlinear wireless communication channel. The performance of the equaliser is measured in terms of Symbol Error Rate (SER), that is, the number of misclassified symbols. The NARMA10 task (Atiya and Parlos 2000) constists in emulating a nonlinear system of order 10. The performance is measured in terms of Normalised Mean Square Error (NMSE).

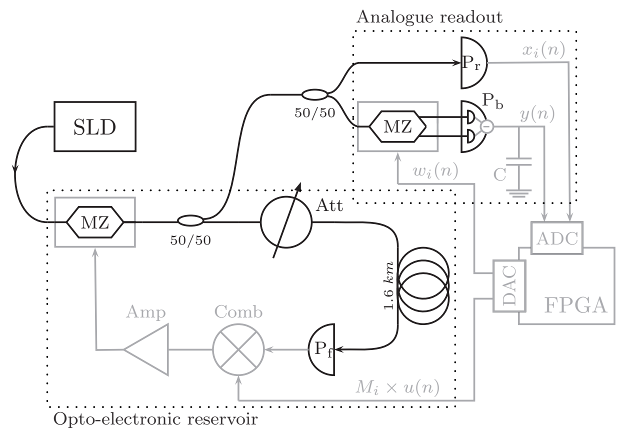

Figure 1: Scheme of the proposed experimental setup. The optical and electronic components are shown in black and grey, respectively. The reservoir layer consists of an incoherent light source (SLD), a Mach-Zehnder intensity modulator (MZ), a $50/50$ beam splitter, an optical attenuator (Att), an approximately 1.6 km fibre spool, a feedback photodiode (P_f), a resistive combiner (Comb) and an amplifier (Amp). The analogue readout layer contains another $50/50$ beam splitter, a readout photodiode (P_r), a dual-output intensity modulator (MZ), a balanced photodiode (P_b) and a capacitor (C). The FPGA board generates the inputs and the readout weights, samples the reservoir states and the output signal, and trains the system.

Experimental setup

Our experimental setup, which we simulate numerically, is schematised in figure 1. It consists of the opto-electronic reservoir (a replica of (Paquot et al. 2012)), the analogue readout layer, based on previous works (Smerieri et al. 2012; Duport et al. 2016), and the FPGA board, performing the online training (Antonik et al. 2016a). The readout layer uses a dual-output Mach-Zehnder modulator in order to apply both positive and negative readout weights, and the integration (summation) of the weighted states is carried out by a low-pass RC filter.

Results

All numerical experiments were performed in Matlab, using a custom model of a reservoir computer, based on previous investigations (Paquot et al. 2012; Antonik et al. 2016a).

The performance of our system on the channel equalisation task, with SERs between 10^{-4} and 10^{-3} depending on the input mask, is comparable to the same opto-electronic setup with a digital output layer (SER $= 10^{-4}$ reported in (Paquot et al. 2012)), as well as the fully-analogue setup (Duport et al. 2016), also reporting SER of 10^{-4}. However, it outperforms the first (and, conceptually, simpler) readout layer by an order of magnitude (Smerieri et al. 2012). As for the NARMA10 task, we obtain a NMSE of 0.18. This is slightly worse than what was reported with a digital readout layer (0.168 ± 0.015 in (Paquot et al. 2012)), but better than the fully analogue setup (0.230 ± 0.023 in (Duport et al. 2016)).

Another goal of the simulations was to check how the online learning approach would cope with experimental difficulties encountered in previous works (Smerieri et al. 2012; Duport et al. 2016). To that end, we considered several potential experimental imperfection and measured their impact on the performance.

- The time constant $\tau = RC$ of the RC filter determines its integration period. We've shown that both tasks work well in a wide range of values of τ, and knowledge of its precise value is not necessary for good performance (contrary to (Duport et al. 2016)).
- The sine transfer function of the readout Mach-Zehnder modulator can, in practice, be biased due to temperature or electronic drifts of the device. This could have a detrimential impact on the readout weights. We've shown that precompensation of the transfer function is not necessary, and that realistic drifts of the bias wouldn't decrease the performance of the system.
- The numerical precision of the readout weights, limited to 16 bits by the DAC, could be insufficient for correct output generation. We've shown that resolution as low as 8 bits is enough for this application.

Perspectives

The present work shows that online learning allows to efficiently train an analogue readout layer despite its inherent complexity and practical imperfections. The upcoming experimental validation of this idea would lead to a fully-analogue, high-performance reservoir computer. On top of considerable speed increase, due to the removal of the slow digital post-processing, such device could be applied to periodic or chaotic signal generation by feeding the output signal back into the reservoir (Antonik et al. 2016b). This work is therefore an important step towards a new area of research in reservoir computing field.

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References

Antonik, P.; Duport, F.; Hermans, M.; Smerieri, A.; Haelterman, M.; and Massar, S. 2016a. Online training of an opto-electronic reservoir computer applied to real-time channel equalization. *IEEE Transactions on Neural Networks and Learning Systems* PP(99):1–13.

Antonik, P.; Hermans, M.; Duport, F.; Haelterman, M.; and Massar, S. 2016b. Towards pattern generation and chaotic series prediction with photonic reservoir computers. In *SPIE's 2016 Laser Technology and Industrial Laser Conference*, volume 9732, 97320B.

Atiya, A., and Parlos, A. 2000. New results on recurrent network training: Unifying the algorithms and accelerating convergence. *IEEE Transactions on Neural Networks* 11(3):697–709.

Duport, F.; Smerieri, A.; Akrout, A.; Haelterman, M.; and Massar, S. 2016. Fully analogue photonic reservoir computer. *Sci. Rep.* 6:22381.

Jaeger, H., and Haas, H. 2004. Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication. *Science* 304:78–80.

Lukoševičius, M., and Jaeger, H. 2009. Reservoir computing approaches to recurrent neural network training. *Comp. Sci. Rev.* 3:127–149.

Maass, W.; Natschläger, T.; and Markram, H. 2002. Real-time computing without stable states: A new framework for neural computation based on perturbations. *Neural comput.* 14:2531–2560.

Paquot, Y.; Duport, F.; Smerieri, A.; Dambre, J.; Schrauwen, B.; Haelterman, M.; and Massar, S. 2012. Optoelectronic reservoir computing. *Sci. Rep.* 2:287.

Smerieri, A.; Duport, F.; Paquot, Y.; Schrauwen, B.; Haelterman, M.; and Massar, S. 2012. Analog readout for optical reservoir computers. In *Advances in Neural Information Processing Systems*, 944–952.

Soriano, M. C.; Brunner, D.; Escalona-Morán, M.; Mirasso, C. R.; and Fischer, I. 2015. Minimal approach to neuro-inspired information processing. *Frontiers in computational neuroscience* 9.

Vinckier, Q.; Bouwens, A.; Haelterman, M.; and Massar, S. 2016. Autonomous all-photonic processor based on reservoir computing paradigm. In *Conference on Lasers and Electro-Optics*, SF1F.1. Optical Society of America.