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Spatio-temporal photonic liquid state and extreme learning machines

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14. ABSTRACT

In this work, we proposed the Bayesian optimization algorithm for tuning the hyper-parameters in large-scale photonic reservoir computers. We tested this approach on a previously reported experimental system, applied to a challenging task in computer vision where 91.3% and 99% accuracy in image recognition of video clips from standard image recognition databases KTH and MNIST used to verify the performance of the developed Photonic Recurrent Neural Network (RNN). We also compared the results with the grid search and Bayesian optimization of the Photonic RNN, commonly used by the non-photonic RNN Computational (RC) community. We report improvements in terms of (1) the classification performance , with an improvement in accuracy of up to 4%, and (2) the convergence time to the optimal set of hyper-parameters, with a roughly 30% reduction in time (that could be doubled for a less than 1.5% accuracy penalty). Taking into account the proximity of the accuracy of our photonic reservoir computer to the state-of-the-art results on this task, and the experimental hyper-parameters optimization time measured in days, these improvements prove to be precious enhancements of the system performance. Furthermore, extensive exploration of the hyper-parameters space with the Bayesian method offers valuable insights on its underlying structure and the relative importance of the parameters. Considering all the advantages offered by the Bayesian optimization algorithm, it may soon become the new standard approach for the optimization of hyper-parameters in photonic reservoir computing.

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FINAL ACTIVITY REPORT

SPATIO-TEMPORAL PHOTONIC LIQUID STATE AND EXTREME LEARNING MACHINES

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I –Project Objectives and introduction

I.1 – Introduction and context

There have been multiple demonstrations that neuro-inspired systems can achieve computation with high-energy efficiency [Merolla14] while performing complex tasks such as pattern recognition and data mining. The definite objective is to provide learning and cognitive capacities to engineered systems comparable to those of complex neural architectures such as the mammal brain.

Among the many existing cognitive computing proposals, reservoir computing has focused significant attention since its initial discovery a decade ago [Jaeger02]. The main idea is illustrated in Fig.(1a). It consists of a three-layer architecture: (i) an input layer detects the data and transmits it first to the second layer, (ii) a dynamical network with a complex topology including recurring loops, and then to (iii) an output layer. This generic structure, also known as an echo-state network (ESN) [Jaeger04], allows mapping the input data to a higher-dimensional space before being processed by the output nodes, which apply a simple readout function with optimized coefficients (weights) via training. The trained output allows the input to be mapped to its corresponding class. The training is like an artificial neural network, except here, the output is the only part of the reservoir computer to be trained.

Reservoir computing has proven to be particularly effective in complex computation tasks such as spoken digit recognition and time-series (*e.g.*, chaotic, financial) forecasting but was mostly realized in simulations. Physical Implementation of ESN has focused research efforts in the past five years. Photonic systems are promising because of their large bandwidth and integration. However, this technology's main downside is the difficulty of interconnecting many photonics devices together, thus making large photonics reservoirs hard to realize. For this reason, the first optical realization followed the principle of Fig. (1b): A single optical node is used with a time-delay feedback line. The feedback line is taped at different locations, corresponding to the position of virtual nodes, and the taped signals are sent to the output layer for computation. The approach based on optoelectronic configurations with delayed feedback has proven that optical reservoir computers can perform state-of-the-art performance on typical benchmarks from the machine learning community [Appeltant11, Paquot11, Larger12, Martinenghi12]. However, they are limited to simple unidirectional topology and cannot benefit from the computing power of multiple interconnected physical nodes; they also are constrained to process data serially.

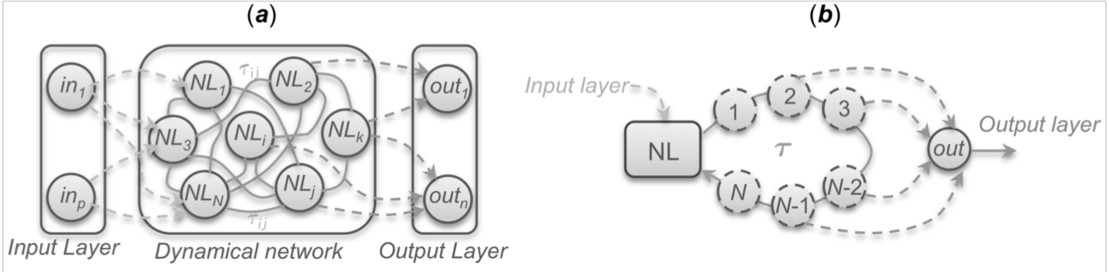

Figure 1 – (a) generic representation of a reservoir computer with p input physical nodes (In1,…,p), a dynamical network with random topology comprising N physical nodes (NL1,…,N) and n output nodes that match the input data to their corresponding class. (b) Physical implementation using a single nonlinear node (electronic or photonic system) (NL) and feedback line with delay τ, where N virtual nodes realizing the function "copy" are placed. The N nodes feed the output layer to classify the input data.

I.1 – Project objectives

The main objective of this project was the continuation of scientific work packages initiated in a previous contract from the AFOSR on optical neuromorphic computing. Our primary motivation with this follow-up project remained to provide novel paradigms of implementations for optical machine-learning architectures (specifically reservoir computing) and develop hardware-friendly optimization and learning strategies to address challenging tasks in computer vision.

We have organized our project in three different work packages:

- Work package 1 (WP1): design and experimental realization of a large-scale spatiotemporal photonic network with thousands of nonlinear nodes as the physical embodiment of a reservoir computer.

- Work package 2 (WP2): Numerical simulation and theoretical analysis of the photonics integration of a reservoir computer for optical telecom applications.

- Work package 3 (WP3): Design and analysis of online training procedure for photonics reservoir computing with fully analog output (as most design relies on batch training and digitalization of system's states and output) and of hardware-friendly methods.

II - Scientific/Technical Results

II.1 - First Work Package: Design of a large-scale photonics networks

We have proposed a photonics-based architecture within the framework of this work package, which implements a recurrent neural network (RNN) under the *reservoir computing* paradigm: a set of machine learning methods to design and train artificial neural networks. The underlying idea is to exploit the dynamics of RNN to process input data by only training the linear output layer. As a result, the training procedure is considerably simplified (a linear regression) while ensuring state-of-the-art performance. Usually experimental limitations, the size of such networks rarely surpasses hundreds of nodes. While large-scale networks, with thousands of neurons, are more challenging to implement, they offer key advantages in terms of parallelism and speed. The original goal of this work package was to implement large-scale parallel reservoir computers with potentially >10,000 nodes.

The design of the system is shown in Fig. 2. This architecture was adapted for reservoir computing application from the setup presented in [Haegerstrom12] used to study collective phenomena in complex networks. We remind that it consists of a spatial light modulator (SLM) with 262,144 pixels. Each pixel can locally modify the optical phase of an incoherent light-beam generated by a LED emitting at 532 nm. The phase values, defining the state of the neurons, are then transformed into intensities using polarized optics and detected by a high-speed camera. A computer mixes the intensities randomly before using them to update simultaneously (and hence in a massively parallel fashion) the phase-state of each neuron. The setup of Fig. 2 shows such a large-scale photonics RNN with up to 16,384 neurons.

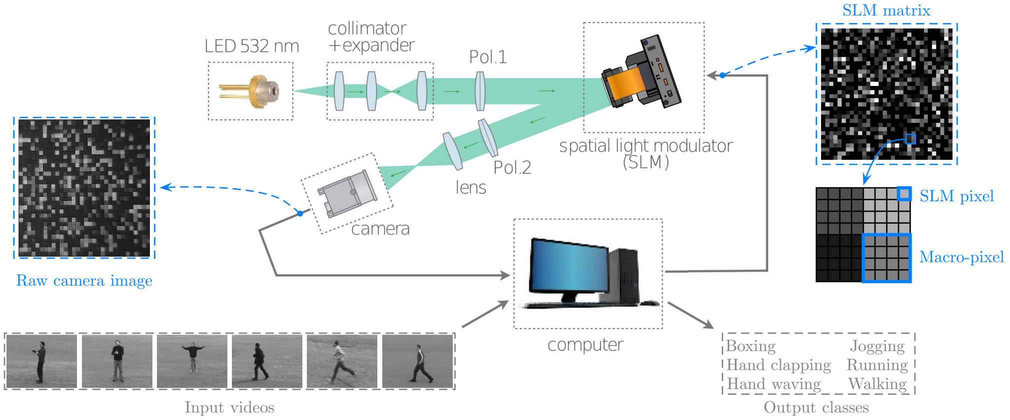

Figure 2 – Illustration of the photonics-based system to create a photonics recurrent neural network with random topology for automatic analysis of human action in video recordings. SLM: spatial light modulator. Pol.: polarizer. Adapted from [Antonik2019].

The system was used as a photonic-based classifier on (i) the popular KTH database, which contains video recordings of 6 different human motions (*i.e.* walking, jogging, running, boxing, hand waving, and hand clapping) performed by 25 subjects and also on (ii) the MNIST database, which contains 27x27 pixels images of handwritten digit from “0” to “9”

The research team has investigated the scalability of their approach, both numerically and experimentally, with network sizes ranging from 1,024 to 16,384 nodes and report classification accuracy as high as 91.3% on the KTH task and as 99% on the MNIST task (NB: the MNIST task is a typical benchmark used in computer vision consisting of 32x32 pixels image of handwritten digits from 0 to 9 [Lecun13]). These two results are comparable to state-of-the-art in the literature using advanced machine learning technique, including deep learning. Best reported performance in the literature on the KTH database is 95.6% success rate and on the MNIST 99.77%.

The results of this WP were published in high impact journals :

The editorial board of the IEEE Journal of Special Topics in Quantum Electronics (JSTQE) has published our work on the MNIST task as an invited paper on the special issue on “Photonics for Deep Learning in Neural Computing” (doi: https://doi.org/10.1109/JSTQE.2019.2924138)
Our results on the automatic video classification has been published in Nature Machine Intelligence and recently highlighted in a News and Views (doi: https://doi.org/10.1038/s42256-019-0124-2)
This work has been presented also in international workshop and conference (oral presentation and invited talks. See full list at the end of the report)

II.1.2 Physical Optimization of Bayesian Optimization

A current line of research is developing a systematic optimization procedure on the experimental Photonics RNN to improve its overall performance on image and video classification tasks while minimizing extensive exploration of the hyper-parameter space. This approach was mainly motivated by the time cost in evaluating the loss function to perform the training.

Our main result showed that coarse Bayesian optimization outperformed a common grid-search of the parameter space systematically with choices of resolution of the hyper-parametric space. Figure 3 shows an example of performance comparison between grid-search and Bayesian optimization on our photonic reservoir computing when solving the classification task on the KTH database. During this study, we also managed to understand better the effect of each hyper-parameter (namely feedback gain, input gain, network interconnectivity, spectral radius) on the overall performance of our reservoir computer. We conclude that the feedback gain and input gain are critical parameters that induce the largest variability in the classification's performance compared to the matrix connectivity and spectral radius. Bayesian optimization for the optimization of reservoir computers has also been proposed by other research teams in numerical and theoretical analysis (see for *e.g.* [Griffith19])

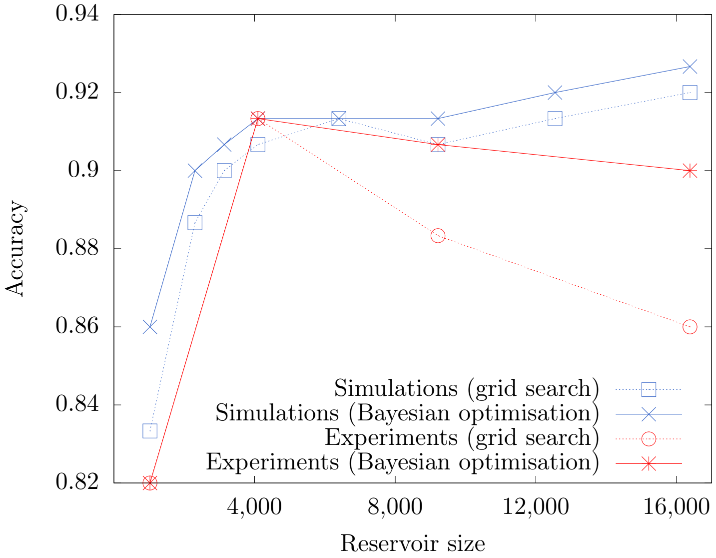

Figure 3 –Comparison of the performance of the photonic reservoir computer developed in WP1 (Fig. 1) on the KTH classification task using grid-search optimization vs Bayesian optimization for the choice of the hyper parameters. Performances are also evaluated for the two optimization strategies as a function of the number of physical nodes in the photonic reservoir computer. Adapted from [Antonik2021]

This work has been published in the journal Cognitive Computing (for a special issue in "Challenges in reservoir computing" (doi: https://doi.org/10.1007/s12559-020-09732-6)

II.1.3 Comparative performance analysis of coherent and incoherent photonic reservoir computers

It is possible to modify the physical setup in WP1 to reduce the amount of electronic-based operation in our architecture. One way to proceed would be to realize the optical summation of various signals using a diffusing element rather than the electronic mixing currently realized as proposed by other teams [Bueno18, Dong19]. It would also require a light source change from an incoherent LED to a coherent laser. When propagating through the diffusive element, the coherent optical signal generates a random speckle pattern, effectively coupling the pixels of the SLM together in a non-trivial random fashion. It will allow alleviating the electronic operation currently performed on our setup significantly. The comparison of the two setups is shown in Fig. 4.

This task proposes a theoretical/numerical performance comparison between the incoherent and coherent reservoir computers with a minimal structural difference. We assess the choice of optical source impact on various tasks such as image/video classification and memory capacity (*i.e.*, a typical task quantifying the ability for a machine learning architecture to replicate accurately input samples time-shifted in the past given current data samples).

Our findings show that the two setups behave with a similar level of performance on practical tasks. However, the choice of hyper-parameter leading to the optimal results differs (as the underlying mathematical models are different for each setup). The range of parameters leading to the best level of performance of the incoherent setup was generally more comprehensive than a coherent setup. The memory capacity and overall resilience to additive noise (intensity noise) were better with the incoherent architecture. Ultimately, this study illustrated the trade-off between performance and alleviation of computation by physical coupling when switching from an incoherent to a coherent light source.

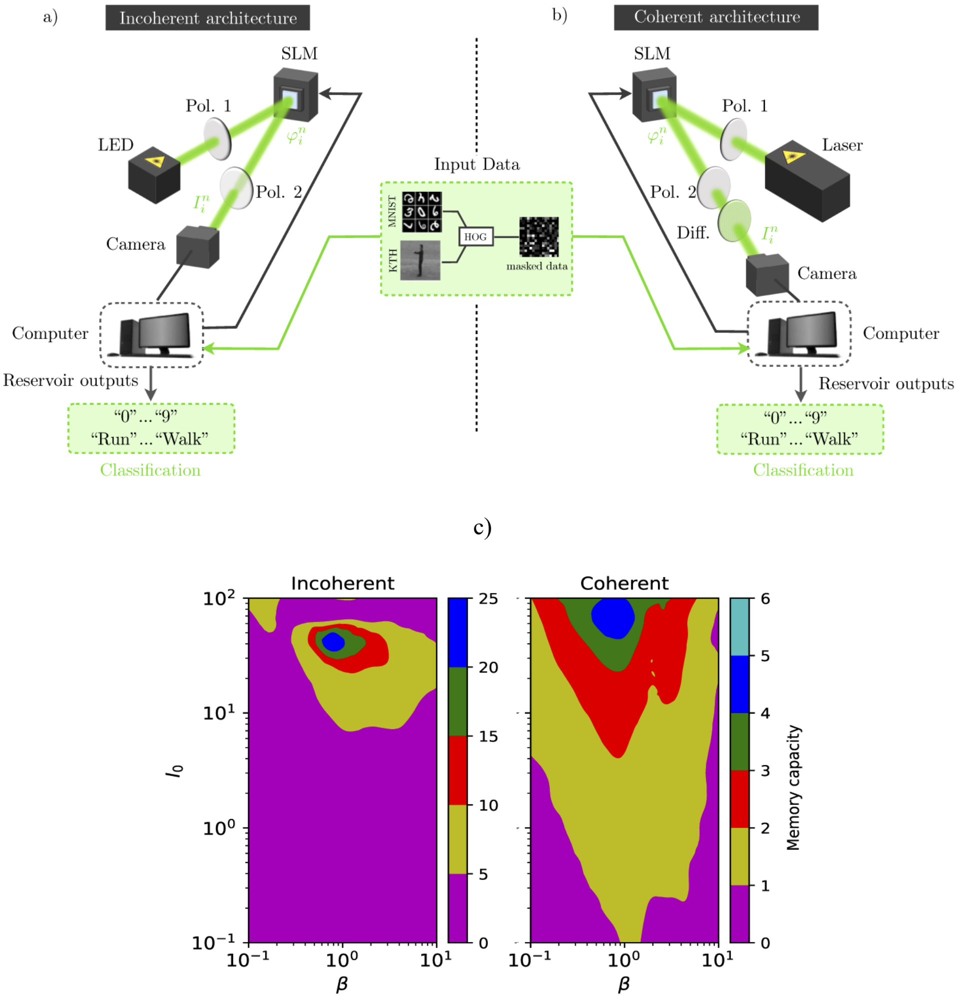

Figure 4 – Illustration of two theoretical architectures of large-scale photonic reservoir computers (a) incoherent setup with a LED, two polarizers (Pol. 1,2), a spatial light modulator (SLM), a camera, and a computer to create the reservoir state-mixing digitally. This setup was implemented experimentally during the grant (b). The coherent setup is based on a coherent light source to ensure structural similarity still uses the two polarizers, a diffusive element that provides non-reconfigurable optical coupling studied theoretically similar to proposals in Ref. [2,3]. (c) illustration of comparative performance on the memory capacity (MC) of the two architecture illustrating the significant difference in achievable MC (by almost one order in magnitude) in favor of the incoherent architecture. The mapping is realized in the plane (I0,β)

corresponding to the optical intensity of the light source and feedback gain, respectively, which are two tunable parameters of the architectures. Adapted from [Nguimdo2020].

Conclusion: This work has been published in the journal Optics Express (doi: https://doi.org/10.1007/s12559-020-09732-6) and was highlighted in OSA Publishing spotlight in October 2020 (https://www.osapublishing.org/spotlight/summary.cfm?id=437982)

II.2 - Second Work Package: Design and simulation of integrated photonics reservoir computing

This work package has investigated an optical reservoir computer integrated on a Silicon-based photonic integrated chip with numerical simulations. The main goal was the numerical simulations of architecture to perform binary-headers recognition of optical packets at speed >20 Gb/s. Our current target application is 5-bits header recognition. We have concentrated our effort on modifying an existing 4x4 swirl-topology architecture composed originally of purely passive components (power splitters and power combiners) [Vandoorne14]. The modification we proposed consisted of an integrated photonic reservoir comprising nonlinear micro-ring resonators as nonlinear photonic nodes and interconnected via cm-long planar waveguides. This study is realized in collaboration with scientists at the University of Ghent (Belgium), and this work package concentrates exclusively on design aspects and system.

We are currently investigating the impact of internal nonlinearity brought by either micro-ring resonators or semiconductor optical amplifiers (SOA) on a swirl-topology network. This type of architecture is illustrated in Fig. 5.

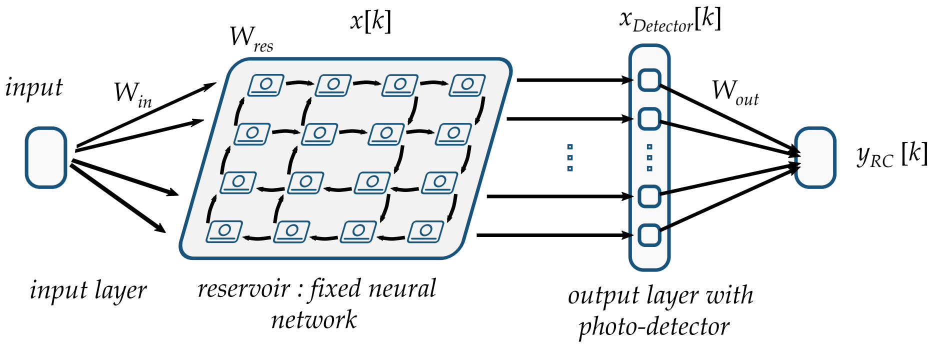

Figure 4 – Schematic illustration of an integrated architecture using micro-ring resonators in a 4x4 SWIRL topology. The interconnection is realized with cm-long planar waveguides and represented by directed arrows. The SWIRL topology has recurrence necessary for reservoir computing and ensures efficient mixing of input data. It also avoids too many connections, which are detrimental from a power budget perspective because of the radiated loss in planar combiners. The readout layer comprises an array of photodetector that produces electrical signals, which are then adequately weighted (after training) and summed to form the output of the photonic reservoir.

We have investigated learning strategies for all-integrated photonics devices using optical intensities, photo-detected (real-valued) signals. This is also referred to the *electrical-domain training*. We have focused on electrical domain training and test the performance of a 4x4 SWIRL network (see Fig. 4) on binary-header recognition. An example on 3-bits and 4-bits header classification tasks is provided in Fig. 5. Using 20,000 bits (12,000 for training and 8,000 for testing) we achieve state-of-the-art performance with a bit error rate (BER) $< 2.5\text{x}10^{-4}$, which is which is below the soft decision forward error coding (SD-FEC) limit. We have also shown that the total optical power budget of about 2.4 mW to power the system.

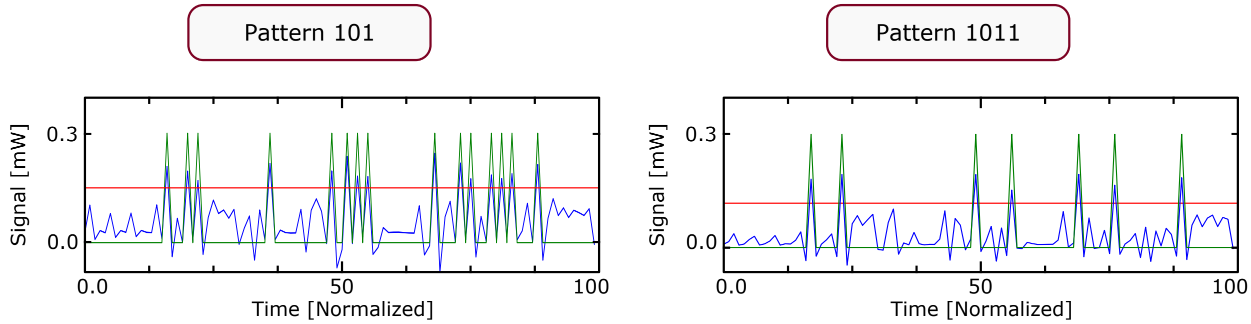

Figure 5 – Example of 3-bits (a) and 4-bits (b) binary header recognition at 20 Gb/s using our micro-ring based integrated reservoir. The green signal represent the target, which spikes when a given pattern (here 101 and 1011 respectively appears in a sequence of 20,000 bits tested). The blue curve represents the trained output of the reservoir and the red solid line the decision threshold used to determine the presence of a pattern. Adapted from [LeCoarer2018].

Conclusion: This work has been published in the journal IEEE Journal of Special Topics in Quantum Engineering (doi: https://doi.org/10.1109/JSTQE.2018.28369.85)

In this work package, we also explored variations in using SWIRL topologies with micro-ring, such as using heterogeneous components such as semiconductor optical amplifier (SOA) and various data injection strategies (*e.g.*, injection of only a subset of micro-ring in the SWIRL topology). However, they did not lead to significant improvement in performance except for a reduction in the optical power budget for the computation. These results were presented in the previous intermediate reports but, in the end, did not lead to published work, so they have not been reported in this final activity report.

II.3 - Third Work Package: Hardware friendly training for analog photonics reservoir computing

In this work package, we have explored approaches to go beyond the well-established linear regression technique used for training digital readout layers of reservoir computers, and investigate advanced algorithms for optimizing analog systems, considered black-box functions. We tested those algorithms on the optoelectronic setup illustrated in Fig. 6, which uses an RC circuit to implement a low-pass filter and perform a fading sum of the reservoir states. These activities have not been published yet and remain confidential and limited to the internal diffusion of this report.

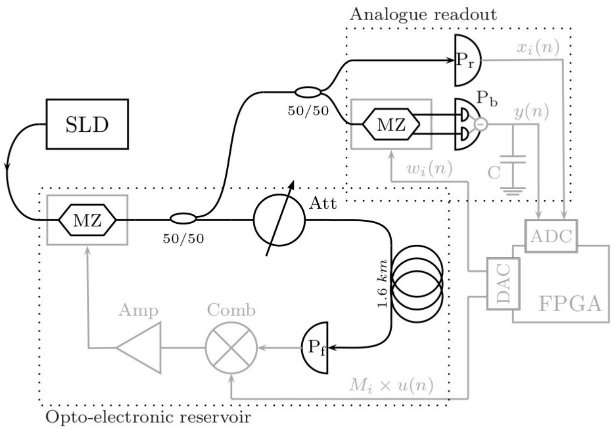

Figure 6 : Experimental setup of a reservoir computer using an optoelectronic oscillator with analog output. SLD: superluminescent laser diode, MZ: Mach-Zehnder modulator, Att.: variable attenuator, Amp. : amplifier, Pr: photo-receiver, Pb: balanced photo-receiver, FPGA: field programmable gate array, ADC : analog to digital converter, DAC : digital to analog converter.

We had focused on the online learning approach based on the simple gradient descent (SGD) algorithm. Online training has attracted much attention in the machine learning community because it gradually trains the system as the input data becomes available. In the case of hardware systems, we have shown that online training can easily cope with drifts in the hardware, as the system will adapt to gradual changes in the hardware components. However, the SGD algorithm assumes the knowledge of the derivative (gradients) of the cost function, which, in practice, is virtually impossible to model in the case of an analog readout layer (*e.g.*, a readout layer using an RC circuit). As illustrated in Fig. 6, does continuous integration rather than an actual discrete weighted sum of the reservoir's state. The experiments had shown that the readout weights did not converge, even when acceleration techniques, such as momentum, were used. It indicates that the gradients computed by the SDB algorithm do not correspond precisely to the shape of the actual cost function we are trying to minimize.

As a promising direction, we focused on the realization and tuning of the fully analogue readout layer. For simplicity, previous experiments with online learning were performed on a semi-analogue system, where the readout weights were applied optically through the second MZ, but the sum operation was performed digitally using a Field Programmable Gate Array (FPGA); see Fig. 6. This step-by-step approach allowed us to isolate the noise induced by the readout MZ, an issue that remains to be solved. Adding the missing RC circuit will allow us to complete the analogue readout layer and to test the new optimization algorithm on the actual experiment, with black-box-like readout function. These results are still under investigation.

III –Project Management and strategic initiative

<u>*III.1 – Management*</u>

Team:

The team is primarily comprised of PI Dr. Rontani and senior personnel co-PI Dr. Marsal. The team has evolved during the grant period: our first postdoc became a permanent staff member at CentraleSupélec and was no longer supported by AFOSR funds. His position as a postdoctoral fellow in our research team has been 12 months instead of the 24 initially scheduled. He was still very active on work-packages WP1 and WP3 and became senior personnel associated with the project.

Following this evolution, we have recruited sequentially four other postdocs and short-term researchers (some of them were partially funded using co-funding from the Conseil Regional de Lorraine). Their contract duration was respectively 22 months (1x), 15 months (1x), and four months (2x) (NB: the last postdocs were former Ph.D. students in our Lab, who worked on purely exploratory topics on WP1 to lay the foundation of future experimental setups for results within the scope of this grant.)

Task Planning:
At the beginning of the grant, during the first year 2017-2018, we initially pursued the lab space organization to continue supporting our research program with new equipment and evolution of the various setups. During 2018-2019, we conducted an intense experimental campaign exploiting our various setups and published impactful journal publications. In 2019-2020, our activity was impacted significantly by the Covid pandemic and complicated access to the Lab. We have then moved towards processing data and conducting numerical studies. We focused our effort on WP1, and WP3 emphasized less on WP2 due to the lack of available workforce in the research team. We plan to build WP2 into a future fully-fledged research program on developing an integrated solution for machine learning and advanced information processing implementation at the physical layer.

Equipment:
Following Dr. Lockwood's approval, we reallocated funding for equipment [saved from purchasing a cheaper version of SLMs (Ajile corp) and high-speed camera (Allied Vision Corp) to buy new equipment to move the entire project forward. The savings realized through these modified purchases have been used to buy optomechanics and optical parts to improve our running setups in WP1. Taking opportunity from a (50%) co-funding offered by the University of Lorraine and the saved funds are sufficient, we bought a larger-resolution SLM to increase even more the size of our slow-speed RNN to the multi-10k nodes. These experiments will be run in the upcoming year due to delays from the Covid pandemic.

III.2 – Scientific production

During the 2017-2021 period, we have produced and communicated multiple results related to WP1, WP2 and WP3. We have presented the results at international conferences and workshops listed below. NB: Underlined authors are supported by the grant.

Invitated talk

D. Rontani *Towards smart Photonics Systems: Scalability, Integration, and Flexibility.* at the international conference ISPALD 2018 (Hong-Kong)

11 Contributed presentations (oral and posters)

F. Denis-Le Coarer, D. Rontani, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, M. Sciamanna, "Reservoir Computing on an active silicon photonics chip using nonlinear micro-rings resonators," Poster presentation at Dynamical systems and Brain inspired computing, Brussels, Belgium, 31 May – 2 June 2017.

F. Denis-Le Coarer, D. Rontani, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, M. Sciamanna, "Nonlinear micro-ring resonators on silicon photonic chip for brain inspired computring," Poster presentation at Dynamics Days Europe, Szeged, Hungary, 5-9 June 2017.

D. Rontani, F. Denis-Le Coarer, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, M. Sciamanna, "Photonics reservoir computing using a small network of nonlinear micro- ring oscillators," Invited talk at Workshop on dynamical systems and brain inspired information processing, Konstanz, Germany, 5-6 October 2017.

D. Rontani, F. Denis-Le Coarer, A. Katumba, M. Freiberger, J. Dambre, P. Bienst- man, M. Sciamanna, "Reservoir Computing with nonlinear micro-resonators on a Silicon photonics chip," Oral presentation at International Symposium on Nonlinear Theory and its Applications NOLTA’17, Cancun, Mexico, 4-7 December, 2017.

F. Denis-le Coarer, D. Rontani, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, and M. Sciamanna, "Toward neuro-inspired computing using a small network of micro-ring resonators on an integrated photonic chip," Oral presentation at SPIE Photonics Europe 2018, Strasbourg, France, April 22-26, 2018.

P. Antonik, N. Marsal, D. Brunner, and D. Rontani, "Performance Analysis of Large- Scale Photonics Reservoir Computers," Oral presentation at International Symposium on Nonlinear Theory and its Applications NOLTA’18, Tarragona, Spain, 2-6 September, 2018.

P. Antonik, D. Rontani , M. Haelterman, and S. Massar, ""Towards Online- Trained Analogue Readout Layer for Photonic Reservoir Computers," Oral presentation at International Symposium on Nonlinear Theory and its Applications NOLTA’18, Tarragona, Spain, 2-6 September, 2018.

P. Antonik, N. Marsal, D. Brunner, and D. Rontani, "Large-scale Spatiotemporal Photonic Networks for Neuro-inspired Image Classification," Poster presentation at Cognitive Computing Conference, Hanover, Germany, December 18-20, 2018

P. Antonik, N. Marsal, D. Brunner, and D. Rontani, "Classification of Human Actions in Videos with a Large-Scale Photonic Reservoir Computer," Poster presentation at International Conference on Application of Neural Networks (ICANN) 2019, Munich, Germany, September 17-19, 2019.

P. Antonik, N. Marsal, D. Brunner, and D. Rontani, "Comparison of Feature Extraction Techniques for Handwritten Digit Recognition with a Photonic Reservoir Computer," Oral presentation at International Conference on Application of Neural Networks (ICANN) 2019, Munich, Germany, September 17-19, 2019.

P. Antonik, N. Marsal, D. Brunner, and D. Rontani, "Large-Scale Photonic Reservoir Computing for Video Processing," Oral presentation at International Symposium on Nonlinear Theory and its Applications NOLTA’19, Kuala Lumpur, Malaysia, December 2-6, 2019.

5 journal publications

[LeCoarer2018] *F. Denis Le Coarer, M. Sciamanna, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, and D. Rontani. ‘‘All-optical reservoir computing on a photonic chip using silicon-based ring resonators’’ IEEE Journal of Special Topic in Quantum Electronics* **24**, *1 (2018)*

[Antonik2019] P. Antonik, N. Marsal, D. Brunner, and D. Rontani, ‘‘*Human actions recognition with a large-scale photonic neuromorphic architecture*’’, *Nature Machine Intelligence* **1**, 530 (2019)

[Antonik2019b] P. Antonik, N. Marsal, D. Brunner, and D. Rontani, *‘‘Scalable Photonic Neural Networks for Image Classification’’ IEEE Journal of Special Topic in Quantum Electronics* **26**, 1 (2019)

[Antonik2021] P. Antonik, N. Marsal, and D. Rontani *''Optimization of large-scale photonic reservoir computers'' Springer Cognitive Computation* 1-9 (2021)

[Nguimdo2020] R.M. Nguimdo, P. Antonik, N. Marsal, and D. Rontani *''Impact of optical coherence on the performance of large-scale spatiotemporal photonic reservoir computing systems'', Optics Express* **28**, 27989 (2020)

III.2 – Strategic Initiatives and Collaborations

During the project, we have pursued an active collaboration with scientists at the University of Ghent (Belgium) related to the study of integrated photonic reservoir computing using nonlinear elements (WP2). This collaboration was established during the previous grant (2016-2017).

We also pursued collaboration with the Université Libre de Bruxelles (ULB, Belgium) on online and adaptive learning of scalable optoelectronic reservoir computers for telecom-oriented applications. It supports a growing activity in WP3, despite not leading to published work during the grant.

We are also pursing a partnership with the Université of bourgogne Franche-Comté via the FEMTO-ST Institute and Centre National de la Recherche Scientifique (CNRS) related to the study of large-scale spatiotemporal networks.

A – References

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