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Scalable Photonic Machine for Neuromorphic Computation-Computational Cognition

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14. ABSTRACT
The main objectives of the project have evolved since the original proposal, and will be detailed below, but they have kept their original motivation of providing novel paradigms of implementations for optical machine-learning architectures and more specifically reservoir computing. The first objective is to design a large-scale spatiotemporal photonic network with several thousands of nonlinear nodes to realize the physical embodiment of a reservoir computer. We have demonstrated in WP2 that the proposed integrated reservoir can perform well on a typical
Boolean task, with very low power consumption. The power budget could even be further reduced in future work by reducing the number of nodes optically injected, for instance by injecting the data only on the four central nodes, as suggested in previous work by some of the authors [Katumba17] with a passive chip. Moreover, from an experimental point of view, it is simpler to inject the data on less nodes, as it reduces the routing density on the chip. Finally, current simulation results are encouraging enough to justify a hardware implementation. This could be envisioned in a near future providing additional funding using the PICs4All European technological platform [Pics4all16], where designs of photonics chips can be realized on demand for research teams at a reasonable cost.
The second objective is to study the possibility of photonics integration of reservoir computer for optical telecom applications. The third objective is to design online training procedure for photonics reservoir computing with full analog output (as most design relies on batch training and digitalization of systems states and output). We have currently programmed the training scheme through a simple gradient descent. Figure 6 shows the preliminary results on a nonlinear task known as the non-linear channel equalization, which consists of

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FINAL ACTIVITY REPORT

Scalable Photonic Machine for Neuromorphic Computation-Computational Cognition

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Topic – "Information Technology" and "Laser & Electro-Optics"

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I – General Introduction & Project Objectives

I.1 Introduction & Motivation

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

Amongst the many existing proposal in cognitive computing, *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 three-layer architecture: (i) an *input layer* detect the data and transmit it first to the second layer (ii) a *dynamical networks* 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 to map 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 for the input to be mapped to its corresponding class. The training is similar to that of an artificial neural network, except here the only part of the reservoir computer to be trained is the output. 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 especially promising because of their large bandwidth and integration. However, the main downside of this technology is the difficulty to interconnect a large number of photonics devices together, thus making large photonics reservoir 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 wire-taped at different locations, corresponding to the position of virtual nodes, and the taped signals are sent to the output layer for computation. This approach using various optoelectronic configurations ith delayed feedback has proven that optical reservoir computers can perform with state-of-art performance on typical benchmark 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 in a serial fashion, but they

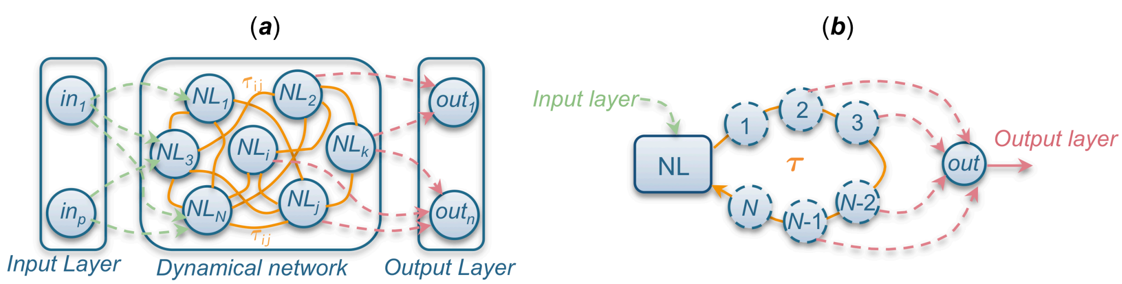

Figure 1 – (a) generic representation of a reservoir computer with p input physical nodes ($in_{1,\ldots,p}$), a dynamical network with random topology comprising N physical nodes ($NL_{1,\ldots,N}$) and n output nodes that match the input data to their corresponding class. (b) Physical implementation using a single nonlinear node (electronic or photonic system) (NL) and feedback time 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.2 Project Objectives

The main objectives of the project have evolved since the original proposal, and will be detailed below, but they have kept their original motivation of providing novel paradigms of implementations for optical machine-learning architectures and more specifically reservoir computing.

The first objective is to design a large-scale spatiotemporal photonic network with several thousands if nonlinear nodes to realize the physical embodiment of a reservoir computer. The second objective is to study the possibility of photonics integration of reservoir computer for optical telecom applications. The third objective is to design online training procedure for photonics reservoir computing with full analog output (as most design relies on batch training and digitalization of system's states and output).

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II - Scientific/Technical Results

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

In this first work package WP1, we have initiated the construction of a photonics-based setup described propose to adapt an existing setup [Hagerstrom12] previously used for the fundamental study of dynamical network and make into a high-speed reservoir computing.

Our proposed dynamical photonic network is shown in Fig. 2. The setup consists of four main components: (i) an laser source at 532 nm (green color) by Coherent, (ii) a high-speed spatial-light modulator (512x512 pixels with refresh rate >300 Hz) by Meadowlark, (iii) a 1.3 Million pixel high-speed camera from Photron (>2000 fps, but exploited in the >100 fps regime), and (iv) an electronic feedback that couples the pixels state of the camera with those of the spatial modulator. Based on Fig. 2, the principle of operation of the photonics network is the following one: a spatiotemporal phase pattern is imprinted by the SLM on the optical beam. The phase pattern is detected by the camera and converted nonlinearly into an intensity pattern. This information is digitized and fed back in real time to specific pixels of the SLM following a specific network topology and thus controlling dynamically the liquid-crystal orientation. This forms a network of photonic pixel described mathematically as coupled maps. Although, each individual component does not have very high speed, the overall bandwidth of the architecture could potentially reach 100 MSymbol/s (where a symbol is coded on 8 or 16 bits depending on the SLM and camera properties).

In our setup, the state of the SLM pixel is given by a phase value (in the interval $[0,2\pi]$ with a 16 bit resolution). Each camera's pixel detects a nonlinear transformation of the SLM phase states through a combination of quarter-wave plate (QWP) and a polarized beam splitter (PBS). The combination of these two polarization-sensitive optical devices allows for a nonlinear phase-to-intensity conversion, which is necessary because the camera is only sensitive to intensity. The output of the polarized beam splitter is imaged by a 4-f optical setup with a ½ reduction factor to accommodate the difference in sensor size between the SLM and the camera. The electronic feedback is currently realized with a computer and Matlab is used to handle the various devices and realize the photonics network. We plan on using a DSP or PFGA board to handle the devices in an future version of the setup to further improve speed. A photo of our current experimental setup is depicted in Fig. 2 (b)-(c). The electronic feedback is also used to realize non-trivial coupling between the various pixels via matrix multiplication. This allows for precise and controllable coupling between pixels (*i.e.* the nodes of the photonics network) but increase the computing load on the non-optical part of the setup. We are considering alternative optical coupling using spatial filtering in the optical domain; the downside being a lack of controllability on the coupling values.

In its current development state, the photonic network is now realized and we need to characterize its performance as a reservoir computer. This task is currently in progress and we will be finalized in the continuing grant awarded to us by the AFOSR. At the moment, we can currently manage to select an area of 50x50 pixels at the center of the SLM and camera, where is illumination is quasi-uniform and has the lowest amount of optical distortion (NB: we use 2" optical elements specifically to avoid such unwanted effects). These pixels represent the accessible nodes of the network. We are currently testing to see if each individual pixel is accessible or if they need to be grouped into macro-pixels to guarantee proper temporal behavior consistent with theoretical models.

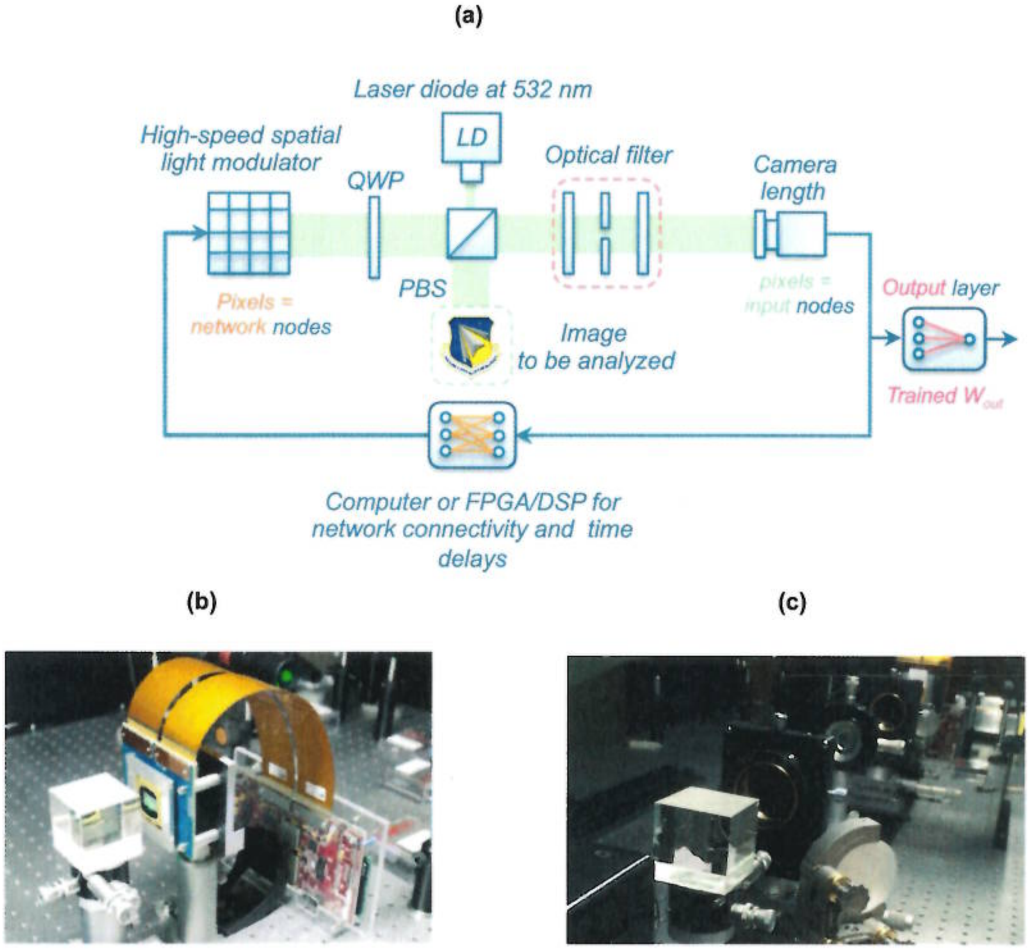

Figure 2 – (a) Proposed setup for the spatiotemporal reservoir computer including an high-speed spatial light modulator, a 4-f optical system, a quarter-wave plate (QWP), a polarized beam splitter (PBS), a laser diode at 532 nm (LD), a high-speed camera, and FPGA/DSP board for network connectivity. The reservoir computer consists of this high-speed photonic reservoir with the addition of an input layer (free port of the PBS or electronic hardwiring at the output of the camera) and the output layer located on the FPGA/DSP board. (b)-(c) Pictures of the experimental setup showing the illuminated spatial-light modulator and the optical arm with the 4-f optical system in front of the high-speed camera.

WP1 has undergone some delay, mainly due to the construction of the entire lab and of the time needed to recruit of people to assemble and test the setup. With the continuing grant awarded by theAFOSR, we will have time to conduct performance analysis on our working setup. We have thus redirected part of our effort in the current grant to WP2 and WP3.

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II.2 - Second Work Package: scalable photonic reservoir computers on a photonic chip

In this work package WP2, we propose a systematic numerical study of an optical reservoir computer integrated on Silicon-based photonics integrated chip. We aim with such structure at recognizing binary headers of information packets circulating in optical networks at ultra-high speed (>10 Gb/s). Our current target application is a 5-bit header recognition. We have for the moment concentrated our effort on the performances of a 4x4 swirl-topology integrated photonic reservoir using non-linear micro-ring resonators as nodes and interconnected via long (cm long) planar waveguide (*i.e*. there is non-negligible transmission delays between nodes). The swirl topology is illustrated in Fig. 3(a) and depiction of non-linear ring is also given in Fig. 3(b). Note that the swirl topology was already proposed in [Vandoorne14] for a microchip made of linear, passive optical devices (optical splitter, combiners, and delay lines).

Figure 3 – (a) illustration of the 4x4 SWIRL topology for interconnected micro-rings. The interconnection are realized with cm-long planar waveguide and represented by directed arrows. The SWIRL topology has recurrence, which is necessary for reservoir computing, and ensures an efficient mixing of input data. This also avoids the use of too many connections, which are detrimental from a power budget perspective because of the radiated loss in planar combiners. (b) Illustration of a micro-ring. The typical sizes used in our simulation are a radius of 4 µm, a waveguide cross-section of 540x220 nm, and an approximate Q factor of 2-3x10^4. The quantity "a" represents the optical mode (phase and amplitude) in the microring (one of the state variable of the system). Signals "s_{in}" and "s_{out}" are the input and output optical signals, respectively.

This architecture has a small number of nodes in our current approach, but remains scalable. However, it still suffers from power management issues (due to losses in the waveguide 3 dB/cm and to the planar combiner losing 6 dB of power by evanescent radiation). Nevertheless, this is still a very promising approach for fully-integrated, optical machine-learning implementation with scalable features.

We have analyzed the performances of the proposed integrated reservoir with micro-rings on a classical nonlinear Boolean task (the delayed XOR task) [Vandoorne14] for (i) various designs of the reservoir in terms of lengths of the waveguides between consecutive nodes, and (ii) various injection parameters (injected power and optical detuning). From this analysis, we find that this kind of reservoir can perform - for a large variety of parameters - the delayed XOR task at 20 Gb/s with bit error rates lower than 10^{-3} and an averaged injection power lower than 3.0 mW.

We have based our analysis using the coupled-mode theory (CMT) approach [Fan03] and developed a set of oriented-object Python scripts to simulate numerically the complex nonlinear effects taking place in the silicon micro-ring (such as two-photon absorption, free carrier absorption and dispersion). Each micro-ring is described by four state variables: the optical phase and amplitude of the optical mode in the cavity, the free-carrier concentration, and the temperature difference between the ring cavity and the substrate. They evolve according to four nonlinear ordinary differential equations (ODE) [VanVaerenberg12]. Hence, the full network state representation comprises 84 linearly coupled nonlinear ODEs.

To analyze the performance of the reservoir, we feed bits in the reservoir by injected each node with modulated optical power. We use a return-to-zero (RZ) baseband modulation between two predefined power level, thus corresponding to feed binary data in the reservoir. Because each node can exhibit nonlinear instabilities, the modulation depth and the choice of the optical frequency of the light injected with respect to the intrinsic resonance frequency of each micro ring is of critical importance. We have computed a stability diagram (with continuation techniques) in the plane of optical injection / optical detuning for a single micro-resonators. Because of the linear optical coupling between the micro-rings in the network, our analysis can be reduced to the stability properties of a single node to then infer the combination of injection parameter that will lead to stable operating point with rich transient features for the entire network. We found the optimum injection power for reservoir computing corresponds to exploiting each micro-ring resonators close to its instability, which is reminiscent of prior work on exploiting dynamical systems at the edge of instability to unlock their computing power [Bertschinger04].

The XOR task under consideration consists of producing the following binary signal y[k] = XOR(x[k], x[k-1]) with consecutive bits x[k] and x[k-1]. To train the linear output of the reservoir to match y[k] based on input x[k], we perform a regularized ridge regression on 16,000 bits send to the various node, and we use the SciKit-learn library of Python [Scikit16]. The testing is then done on the 4,000 remaining bits, on the best case resulting from the five-fold cross-validation. We report the error rates on the test data; hence, the minimum measurable error rate is 2.5×10^{-4}. Multiple-input simulations are performed with the same bit stream injected with the same input weights on all 16-nodes. For the readout layer, we use also the states of all 16-nodes to perform the training and the testing of the reservoir.

Among the various tunable and design parameters of the network, we have identified that the inter-delay connection must be approximately 20 ps for optimal level of performance – This inter-delay value is commensurate with the fastest intrinsic time-scale of the micro-ring resonator. For the targeted 20 Gb/s data rate, as shown in Fig. 4(a)-(b), we also found that the optimal level of input power has to be close to instability with approx. 0.3 mW per node and the optical detuning must be taken out the range of the resonant absorption peak of the micro-ring (typically the detuning is exceed +/- 50 pm).

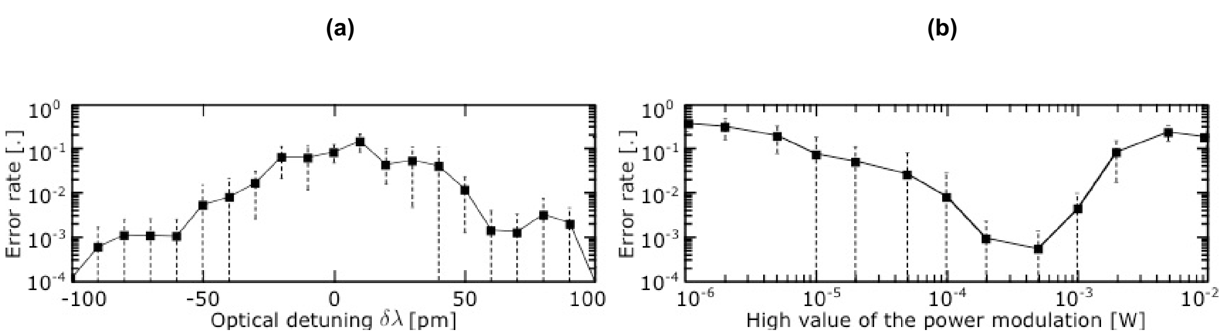

Figure 4 – (a) Error rate - for the XOR task - as a function of the optical detuning for a power modulation between $P_{in,0}$ = 0.0 mW and $P_{in,1}$ = 0.5 mW, an interdelay of 18.75 ps, and a bitrate 20 Gb/s. (b) Error rate as a function of the high value of the power modulation ($P_{in,1}$) for an optical detuning Δλ = 50 pm, an interdelay of 18.75 ps, and a bitrate of 20 Gb/s.Error bars are given for seven series of simulations. The minimum acceptable error rate is 10^{-3}.

We have demonstrated in WP2 that the proposed integrated reservoir can perform well on a typical Boolean task, with very low power consumption. The power budget could even be further reduced in future work by reducing the number of nodes optically injected, for instance by injecting the data only on the four central nodes, as suggested in previous work by some of the authors [Katumba17] with a passive chip. Moreover, from an experimental point of view, it is simpler to inject the data on less nodes, as it reduces the routing density on the chip. Finally, current simulation results are encouraging enough to justify a hardware implementation. This could be envisioned in a near future providing additional funding using the *PICs4All* European technological platform [Pics4all16], where designs of photonics chips can be realized on demand for research teams at a reasonable cost.

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II.3 - Third Work Package: Online training of analogue readout layers in photonic reservoir computers

The major drawback in most experimental implementations of reservoir computing is the absence of efficient readout mechanisms: the states of the neurons are collected and post-processed on a computer, severely reducing the processing speeds and thus limiting the applicability. An analog readout would resolve this issue. This research direction has already been investigated experimentally in [Smeieri12, Duport16, Vinckier16], but all these implementations suffered from significant performance degradation due to the complex structure of the readout layer.

In this work package WP3, we address the above issues with the online learning approach. Online training has attracted much attention in the machine learning community because it allows training the system gradually, as the input data becomes available. In the case of hardware systems, online training can easily cope with drifts in the hardware setup, as the system will adapt to gradual changes in the hardware components. The important point in the present context is that, compared to previously used offline (batch) methods, in online training based on gradient descent, no assumption is necessary about how these weights contribute to the output signal. That is, it is not necessary to model the output layer. Furthermore, the transfer function of the readout layer could in principle be nonlinear.

Promising numerical proofs of these ideas have been published in [Antonik17]. The current step in this work package is to demonstrate the benefits of online learning experimentally. We have first decided to test this concept on a simple time-delay photonic reservoir computer (see Fig. 1(b)) known as the optoelectronic oscillator. So far, we have realized the experimental setup, based on [Smeieri12] and [Pacquot12] and depicted in Fig. 5. This consists comprising a telecom laser source (SLD), a Mach-Zehnder modulator (MZ), which provides the nonlinearity in the system, a long optical fiber of 1.6 km to realize the delay lines, an optical attenuator (Att) to control the feedback gain, a photo-detector (Pf) and a band-pass filter (Amp) that control the voltage of the RF port of the MZ. In addition, we have proposed an analog readout layer comprised of a two-output MZ and balanced photo-diode (Pb) followed by a capacitor (C), which allows for the analog summation of each state (corresponding to delayed states sampled at different time in the delay line). Each delayed state is multiplied by the correct weighting factor calculated by an online optimization algorithm implemented directly on an Field Programmable

Gate Array (FPGA) board Xilinx Virtex 6 and converted into an analog voltage signal by a digital-to-analog converter (DAC) applied to the RF port of the MZ in the output layer. An analog-to-digital converter (ADC) is needed to control the value of the analog output and ensure the proper behavior of the output layer.

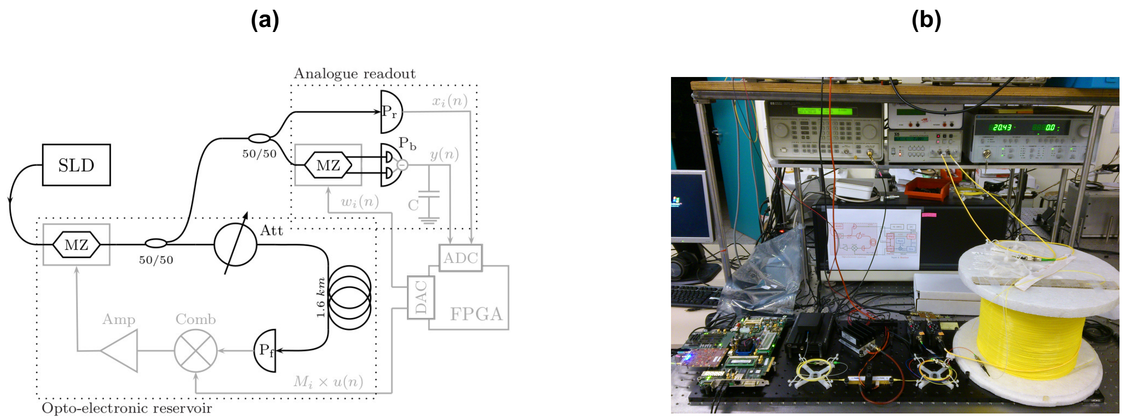

Figure 5 – (a) Proposed setup for an optical reservoir computer based on an optoelectronic oscillator with an analog output layer and an FPGA board for hardware online training. SLD: semi-conductor laser diode, MZ: Mach-Zehnder modulator, Att : optical attenuator, Pf, Pr : photodiode, Amp : band-pass filter with tunable gain, Pb : balanced photodiode, FPGA : Field-programmable gate array. (b) Photo of the experimental setup in our laboratory, this work is realized in collaboration with Université Libre de Bruxelles (ULB), Belgium.

We have currently programmed the training scheme through a simple gradient descent. Figure 6 shows the preliminary results on a nonlinear task known as the non-linear channel equalization, which consists of binary signal regeneration after propagation in a communication channel (*e.g.*: optical fiber, WIFI) and is thus important for telecom applications. We monitor the symbol error rate on the channel equalization task and observe that it quickly decreases from 0.75 (*i.e.* a random guess by the reservoir for inferring the regenerated symbol) down to 0.01. However, the performance is yet to achieve the target error rates of 10^{-4}, as multiple system's parameters still need to be optimized in this experiment. We plan on conducting more thorough analysis in the continuing grant given by the AFOSR. We also plan on applying the online learning strategy to the large-scale photonics network in WP1 and integrated photonics devices in WP2, as such free-space optical setups are known to exhibits drifts over time.

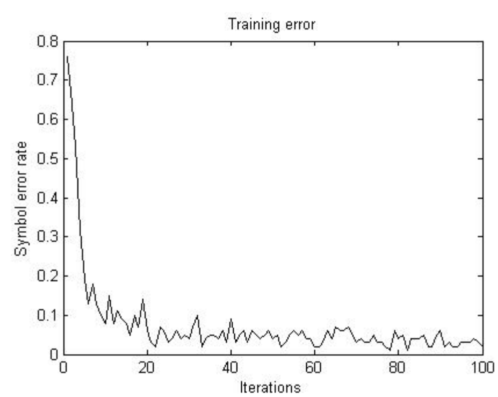

Figure 6 – Evolution of the training error as a function of iteration of the training showing a rapid decay towards symbol error rate <0.01 in the nonlinear channel equalization task.

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III –Project Management and strategic initiative

III.1 – Management

The project started with the first review meeting with the annual review in Arlington, VA for the "Computational Cognition and Machine Intelligence program" in November 2015. The creation of a dedicated lab space to support the research of the grant started early 2016, when funding was made available. We have arranged a fully equipped $20m^2$ research space specifically dedicated to studies on photonics implementation of machine learning concepts in direct relation with the AFOSR grant. This initial step has taken more than 12 months to have a lab space to be operational. A picture of the space as of October 2017 is given in Fig. 7.

Figure 7 – Picture of the lab space at CentraleSupélec and managed by Dr. Rontani. This lab space has been built specifically to conduct research supported by the current and continuing grants given by the AFOSR on photonics neuro-inspired computing.

In October 2016, WP1-WP3 started. In April 2017, we identified Mr. Antonik (then a PhD candidate) for a postdoctoral position in real-time implementation of machine learning concepts. Mr Antonik worked on the current grant and on the continuation grant awarded by the AFOSR. Funding in personal from the grant was secured to pay for the first months of his postdoctoral position (the continuing grant being used to prolonged research on optical machine learning). The preparation of his recruitment at

CentraleSupélec required the funding to be pre-allocated to establish the contract and pay the wages, and hence allowing us to use the grand money in prior to the end of grant. In October 2017, Dr. Antonik joined our team directly from the Université Libre de Bruxelles (ULB, Belgium) and has started working on various machine-learning concepts for WP1 and WP3 such as the large-scale spatiotemporal reservoir computer and hardware implementation of online training.

We have redefined our research effort during the 2016-2017 period based on what we considered to be the most promising direction within the broad context of the project of producing scalable photonics machine for neuro-inspired computation. Preliminary studies on photonics integration of scalable architectures are in our opinion one of the growing and critical field for future development of commercial photonics-based machine-learning solutions. This is why we have devoted some time on their numerical simulations to prepare future hardware implementations (upon available funding). Our large-scale spatiotemporal platform, however, allows us to test more fundamental concepts related to learning and emergence of cognition in networks of photonics-based dynamical systems.

III.2 – Scientific production

During the grand period, we have produced and communicated multiple results related to WP2. We have presented the results at international conferences and workshops listed below:

1 poster presentation at the workshop "Dynamical System and Brain Inspired Computing" (Brussels, Belgium)

Nonlinear microring resonators on silicon photonic chip for brain inspired computing
Florian Denis-le Coarer, Damien Rontani, Andrew Katumba, Matthias Freiberger, Joni Dambre, Peter Bienstman, Marc Sciamanna

1 poster presentation at the international conference "Dynamics Days Europe" (Szeged, Hungary) :

Reservoir computing on an active silicon photonics chip using nonlinear microrings resonators
F. Denis-le Coarer, D. Rontani, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, M. Sciamanna

1 invited talk at the workshop "Dynamical Systems and Brain-inspired Information Processing" (Konstanz, Germany)

Photonics Reservoir Computing Using a small network of nonlinear Micro-ring oscillators
D. Rontani, F. Denis-le Coarer, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, M. Sciamanna

1 invited talk at the international conference "NOLTA" (Cancun, Mexico)

Reservoir Computing with Nonlinear Micro-Resonators on a Silicon Photonics Chip
D. Rontani, F. Denis-le Coarer, A. Katumba, M. Freiberger, J. Dambre, P. Bienstman, M. Sciamanna

There is also **1 paper in preparation** to be submitted to the *IEEE Journal of Selected Topics of Quantum Electronics*.

We have also submitted for **two invited oral presentations** for a Special Session and of the 2018 edition of the NOLTA conference on preliminary results on WP1 and WP3 (these results are also possible thanks to the continuation grant from AFOSR):

Towards online-trained analogue readout layer for photonic reservoir computers (for WP3)
P. Antonik, D. Rontani, M. Haelterman, S. Massar

Performance of large photonics networks for reservoir computing (for WP1)
P. Antonik, N. Marsal, D. Brünner, D. Rontani

III.2 – Strategic Initiative

During the grant period, we have leveraged our existing lab space on photonics-based machine learning and our growing expertise to start strategic collaboration with European collaborators.

We have initiated a fruitful collaboration with scientists at the University of Ghent (Belgium) related to the study of integrated photonics reservoir computing using nonlinear elements. This collaboration supports our activities in WP2. We have leveraged their knowledge of Silicon Photonics chip and machine learning with our competence in nonlinear dynamics and machine learning to propose novel designs with nonlinear micro-rings for the design of reservoir computers. This partnership has growing steadily and started in October 2016.

We have initiated collaboration with the Université Libre de Bruxelles (ULB, Belgium) on topics related to online and adaptive learning of scalable optoelectronic reservoir computer for telecom-oriented applications. This supports our growing activities in WP3. This partnership has growing steadily with the arrival of our Postdoctoral researcher in October 2017.

We have also initiated a partnership with the Université of Franche-Comté and Centre National de la Recherche Scientifique (CNRS) to develop activities related to the training of fully analog output layer for large-scale spatiotemporal networks. This partnership has started in November 2017.

Thanks to the AFOSR grant, we have also succeeded in receiving competitive match-funding grant by our local state (the Region Grand-Est in France). As a result, we have received an additional 20 k€ in December 2017 to further support our current postdoctoral researcher on large-scale spatiotemporal neuromorphic computing in addition to the current AFOSR grant.