Integrated optical output layer for a reservoir computer based on frequency multiplexing

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ABSTRACT

Reservoir Computers (RCs) are brain-inspired algorithms based on recurrent neural networks where only output weights are tuned, while internal weights remain untrained. We recently demonstrated a photonic frequency-multiplexing RC encoding neurons in the lines of a frequency comb. We also demonstrated a single-layer feed-forward neural network based on a similar frequency-multiplexing principle. Here we present the design for an integrated optical output layer for such frequency multiplexing based photonic neural networks. The all-optical output layer uses wavelength (de)multiplexers and wavelength converters to apply signed weights to neurons encoded in comb lines.

Keywords: Reservoir computer, Optical neural network, Optical frequency comb, Wavelength converter, Spectral filter

1. INTRODUCTION

Brain-inspired algorithms, like Artificial Neural Networks, are the key tool for information processing in a plethora of fields such as computer vision and natural language processing, and are already definitively outperforming traditional, digital, computing schemes.[1]

Randomized Neural Networks (RNN) are a class of Artificial Neural Networks where most of the connections among neurons remain fixed and not tuned, while only output connections are trained.[2] This approach has two advantages: first, training only the output weights coincides with a linear minimization problem and does not require iterative algorithms like gradient descent; second, since internal weights are not required to change, RNNs are easily implementable on unconventional substrates, alternative to traditional electronic computers. For their nature, these networks are particularly indicated for signal processing in environments where low-power and low-footprints are priorities, e.g. in edge-computing scenarios.[3]

Photonics is a highly interesting platform for unconventional computing: the ability to manipulate multiple degrees of freedom of the light allows to achieve high-bandwidth computations by employing commercial-grade off-the-shelf devices.[4] We implemented in photonics two RNN algorithms: a feed-forward RNN algorithm, able to perform classification tasks, named Extreme Learning Machine (ELM);[5] and a recurrent RNN algorithm, able to process timeseries, named Reservoir Computer (RC).[6] Both our photonic implementations are based on a substrate exploiting frequency multiplexing, where neurons encoded in the amplitudes of the lines of a frequency comb. These two schemes have been demonstrated in fiber-based experimental setups.[7–9] The natural next step of our work is the integration of the computational substrate on photonic chips, which would improve stability and power-efficiency and reduce the system footprint, thus demonstrating the possibility of employment in real-world

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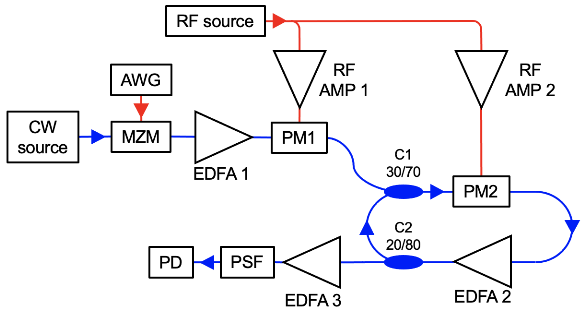

Figure 1: Setup of the fiber-based frequency multiplexing RC. MZM: Mach-Zehnder Modulator; AWG: Arbitrary Waveform Generator; EDFA: Erbium-Doped Fiber Amplifier; RF AMP: Radiofrequency signal amplifier; PM: Phase Modulator; C: Polarization-maintaining fiber coupler; PSF: Programmable Spectral Filter; PD: Photodiode.

applications. Here we present two complementary integrated designs for the manipulation of information encoded in frequency comb lines. The main purpose of this couple of chips is to constitute an optical output layer for our photonic RC scheme, able to apply (signed) weights to neurons and sum their values in the optical domain. The first chip is designed specifically to assign the weights to the neurons, while the second chip contains a SOA-based wavelength converter used to sum the neuron signals, also providing an output non-linearity. Importantly, the same couple of chips could also work with our photonic ELM design: first, they could constitute an optical output layer for the ELM, exactly as in the RC case; second, the filter chip alone could replace a bench-top spectral filter we currently employ in the fiber-based demonstration, speeding up the ELM operation and demonstrating the feasibility of a fully integrated frequency multiplexing ELM. Both the RC and ELM schemes potentially allow for the parallelization of different tasks, executing multiple calculations, each one based on a different frequency comb.[8]

In Sec. 2 we summarize the working principle of our frequency multiplexing RC platform and we describe the fiber-based demonstration; in Sec. 3 we discuss the limit of a fiber-based implementation, and we present the two integrated designs constituting the optical output layer; in Sec. 4 we briefly describe the outlook of our work and report our conclusions.

2. FREQUENCY MULTIPLEXING RESERVOIR COMPUTING

The fiber-based RC setup is schematized in Fig. 1. All the fibers are single-mode and polarization-maintaining. The desired input signal is encoded in a continuous-wave monochromatic laser radiation through a Mach-Zehnder Modulator (MZM) driven by an Arbitrary Waveform Generator (AWG). The monochromatic radiation then gets amplified by an Erbium-Doped Fiber Amplifier (EDFA1) and passes through a Phase Modulator (PM1) which applies periodic phase modulation, with the effect of generating a frequency comb. The spacing of the comb lines is approximately 20 GHz and the number of comb lines having a signal-to-noise ratio high enough to encode information is roughly 20 dB. The light beam is then injected in a fiber loop, around 15 meters long, corresponding to a round-trip frequency of approximately 20 MHz. During each round trip in the fiber loop, the radiation passes through a second Phase Modulator (PM2) and an amplifier (EDFA2). PM2 is driven by the same RF signal driving PM1, thus it generates interference in the frequency domain, mixing information encoded in the comb lines; the EDFA is used to balance the losses in the loop. The timesteps of the external input signal, information to be processed, are synchronized with the loop round-trip time, such that each input timestep completely fills the loop. The frequency comb line amplitudes at the n-th roundtrip represent the state of the reservoir at the n-th timestep. For each roundtrip, 20% of the light intensity is extracted from the fiber loop and redirected toward an optoelectronic readout layer. In this proof-of-concept experiment, the readout layer is composed of an amplifier (EDFA3), a Programmable Spectral Filter (PSF), and a photodiode (PD). The PSF is employed to attenuate each comb line proportionally to the output weight required on that particular neuron. The PD integrates the total comb power after the weighting, thus performing a positive weighted sum. In order to apply both positive and negative output weights, two filters can be employed, one applying positive weights and the other applying negative weights, and a balanced photodiode measures the difference in optical power. In the following, we aim a replacing the optoelectronic readout layer with a photonic integrated one.

3. DESIGN OF THE INTEGRATED OUTPUT LAYER

3.1 Advantages of integration

The current RC fiber-based demonstration is affected by some limits which are a direct consequence of the presence of more than 20 meters of optical fiber, 15 meters of them constituting a loop. The long fiber path exposes the system to acoustical noises and thermal drifts. Currently, the fiber loop is mounted in an insulated box and is actively stabilized. Integration could drastically reduce the length of the optical delay lines, thus notably reducing both the footprint and the influence of noises and drifts, removing the need for insulation and stabilization. Moreover, the data processing speed is inversely proportional to the roundtrip time in the loop delay line, thus a shorter, integrated, delay loop would increase the processing speed. We designed an integrated chip containing a delay loop (0.4 ns roundtrip time, corresponding to 2.5 GHz input rate) including a phase modulator and a Semiconductor Optical Amplifier (SOA) to provide gain, which is currently under testing and not object of this work.[10]

Here we present the design of two chips constituting an integrated programmable spectral filter and a SOA-based wavelength converter, which constitute the two parts of an optical output layer for our RC scheme. These chips are intended to be tested at first on our fiber-based implementation. As a next step, they could be combined with the integrated delay loop already under test, in order to prove the feasibility of a fully integrated frequency multiplexing RC.

3.2 Integrated programmable spectral filter

Our frequency multiplexing scheme is based on the manipulation of information encoded in the lines of optical frequency combs: each line represents a neuron signal. Neuron signals have to be weighted in order to generate the proper output signal, and the weighing operation consists of attenuating each comb line independently.

Our integrated programmable spectral filter is represented in Fig. 2 and is composed of three sections. First, a 1-to-16-channel wavelength demultiplexer, which redirects each comb line on a different waveguide. Second, an attenuation stage composed of 16 attenuators, one per waveguide, able to control each comb line independently. Third, a 16-to-1-channel wavelength multiplexer, which combines each wavelength back into a single waveguide, reconstructing the frequency comb spectrum at the output.

The filter is tailored to the characteristics of the comb currently employed in our fiber-based experiment. As described in Sec. 2, the frequency comb is currently generated by a 20 GHz phase modulation applied to a CW laser radiation. Thus, the target channel spacing of the (de)multiplexer is 20 GHz. This first test of the (de)multiplexer configuration addresses 16 channels, but it is technically possible to increase this number in the future.

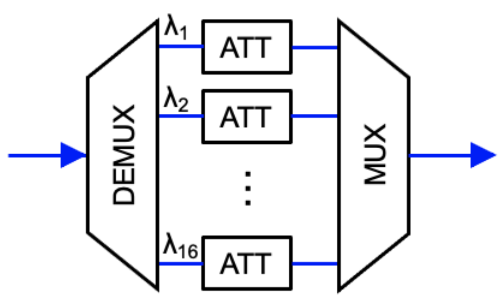

Figure 2: Schematic of the proposed spectral filter. The input signal is an optical frequency comb composed of maximum 16 lines (λ_1, λ_2, ..., λ_{16}). The demultiplexer separates each comb line that are then attenuated individually and multiplexed again in a single waveguide. DEMUX: 1-to-16 wavelength demultiplexer; ATT: Attenuator; MUX: 16-to-1 wavelength multiplexer. Electrical connections to attenuators are not shown.

The performance of the filtering stage will impact the accuracy of the weighting process, and thus will impact the quality of the output signal. We listed four particular aims to keep into account while designing the filter: 1) low and uniform losses among the 16 channels; 2) a flat-top transmission function, which would increase the tolerances towards temperature drifts; 3) high extinction ratio and low cross-talk; 4) no need for active alignment among the different (de)multiplexing stages, to reduce complexity and power-consumption. To accomplish the previous specifications with reliable and mature components, maintaining a small footprint and CMOS compatibility, Silicon Photonics represents the most suitable platform.

The filter needs to manipulate 16 channels over a relatively small free spectral range of approximately 2.2 nm. Most of the literature (de-)multiplexing filters consist of echelle gratings and array waveguide gratings.[11,12] However, these schemes cannot fulfill the previous specifications since it is hard to guarantee low losses and flat-top operation without an active synchronization of cascaded filter stages.

In our case, the integration of flat pass-band filters over a small channel spacing of 20 GHz is obtained by use of a multi-stage lattice filter.[13] The central optical frequency of operation of a lattice filter might vary from chip to chip, due to fabrication uncertainties. However, this has no impact on our system, as we can tune the comb central frequency in order to match the fabricated filter with no expected drawback on RC performance. In addition, the flat-top transfer function of the filter gives ulterior stability against possible tuning misalignment. While a single filter can be aligned with the comb by shifting the comb itself, in situations where two or more filters are employed together (see Sec. 3.4), a more complex alignment is required. In these cases, the simplest solution is to take a filter as a reference, and then, both, shift the comb and heat the other filters to match the reference filter. In the first demonstrators, the weighting is performed via attenuators based on thermo-optic phase shifters in interferometric configuration; we list some interesting possible alternatives in Sec. 4.

3.3 SOA-based wavelength converter

The integrated output layer is required to perform summation of the weighted neuron values, in our case encoded in comb lines. So far, in our fiber-based experiment, the summation occurred by means of photodetection (e.g. through a balanced photodiode) and/or digital post-processing. The currently employed electro-optical conversion of the output signal is easier to realize, but increases the total power consumption and does not reach the fast real-time processing capability of the analog optical domain. Semiconductor Optical Amplifiers (SOA) are optoelectronic devices specifically designed to amplify light without the need for an optical cavity. The change of electrical carrier density in a SOA produces a significant change in the gain and in the refractive index of the active material, thus SOAs are very often employed to perform wavelength conversion or switching functionalities.

Our suggested scheme to perform the optical sum of weighted neuron values is based on a SOA operated in wavelength conversion configuration, as represented in Fig. 3. The frequency comb encoding (weighted) neuron signals is injected in a SOA together with a low-power monochromatic CW "probe" signal at wavelength λ_p. The SOA is operated in the so-called "small-signal" regime: this means that the probe power, P_{probe}, is much lower than the power of the frequency comb. In this situation, the probe does not influence the saturation of the SOA gain, which is only affected by the total comb power, that is the sum of each comb line power, meaning the sum of the signal of each neuron. Consequently, the probe radiation will experience a gain dependent on the sum of all the signals encoded in the comb lines. Note that this process is inherently non-linear, which we expect constitutes an advantage in a neuromorphic computing application. Indium Phosphide represents the most reliable material choice for the fabrication of SOAs, thus we chose this platform for the realisation of the wavelength converters.

3.4 Output layer

A combination of a single spectral filter and a single SOA-based wavelength converter is able to apply unipolar (i.e. unsigned) weights. In order to achieve bipolar (i.e. signed) weighting, two filters and two wavelength converters can be combined as represented in Fig. 4.

In the proposed configuration, the comb to be weighted is split by a 50/50 coupler and supplied to two different filters. The first filter only applies the positive weights and completely attenuates the lines in need to be negative weighed. The second filter, conversely, only applies the negative weights (taken without sign) and

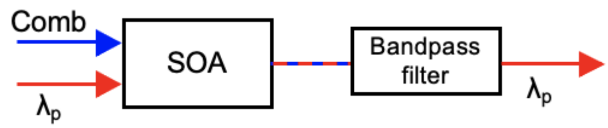

Figure 3: Scheme of the proposed SOA-based wavelength converter. Both an optical frequency comb and a (low-power) probe signal (λ_p) are supplied to the SOA. The SOA gain is saturated by the frequency comb power, and the gain saturation is reflected on the output at the probe wavelength. A bandpass filter (external to the chip) selects only the probe radiation λ_p which encodes a signal dependent on the sum of the signal encoded on each line of the input comb.

completely attenuates the lines in need to be positively weighted. In this way, two combs are obtained at the outputs of the two filters, which we call "positive weighted comb" and "negative weighted comb". Each of the two combs passes through a different wavelength converter, hence the signals contained in their lines get encoded in two monochromatic signals, both coming from the same source at wavelength λ_p. These two signals are made interfere, generating the output of the system.

Since this scheme exploits interferometric effects, an integrated approach is fundamental to minimize the influence of the noise in the phase difference of the two optical paths. As represented in Fig. 5, in a single chip, the probe signal is divided equally in two different branches passing through a 50/50 splitter, afterwards the splitted signals experience the cross gain modulation in the wavelength converters, and finally, by recombining the two paths with a Multi-Mode Interferometer (MMI) the signals are made interfere on chip and extract with the help of a bandpass filter: in this way, the phase differences among the two interfering paths depend only on the path on chip.

Note that a possible solution to avoid the use of a bandpass filter is to inject the probe radiation in a counter-propagating direction with respect to the comb signal. The scheme could be visualized in Fig. 5 inverting the output with the probe.

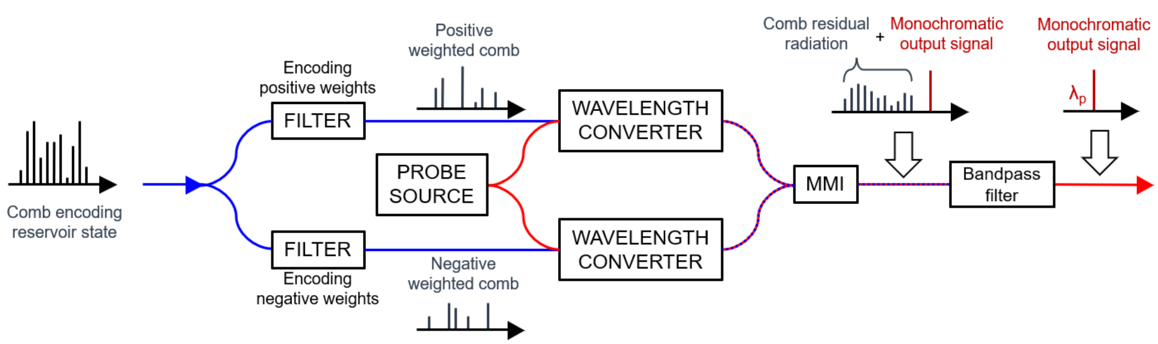

Figure 4: Working principle of the proposed optical output layer. The frequency comb encoding neuron values to be weighted is supplied to two filters. The first filter applies positive weights and blocks the lines that need negative weights; inversely, the second filter applies negative weights and blocks the lines that need positive weights. The two weighted combs are then supplied to two wavelength converters (Fig. 3), thus the content of their neurons is summed and transferred to the probe wavelength λ_p. The two signals at wavelength λ_p are then made to interfere destructively. The residual comb radiation is removed through a bandpass filter. Note that the probe radiation power is lower than the comb power (see Sec. 3.3), hence the representations of the spectrum are not in scale.

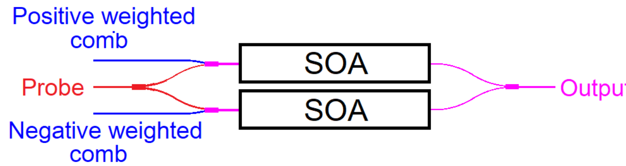

Figure 5: Schematic of the SOAs positioning in our chip design. Small rectangles at waveguide intersections represent MMI couplers/splitters. Note that the difference in phase among the two interfering components of the probe radiation only depends on a difference in optical path generated on chip.

4. SUMMARY AND CONCLUSION

We presented two integrated designs for a spectral filter and a wavelength converter, respectively, which constitute the building blocks of an optical output layer for our Reservoir Computer based on frequency multiplexing. The same integrated tools are employable in other neuromorphic computing schemes where the neuron signals are encoded in the lines of a frequency comb, like in our Extreme Learning Machine scheme.[7] The first chip is a programmable spectral filter based on cascaded lattice filters; the second chip is a wavelength converter based on SOA gain saturation. We also presented a novel scheme to perform, in the optical domain, a signed-weighted summation of neuron signals encoded in the lines of a frequency comb. Future improvements rely upon the hybrid integration of the SOA in Silicon Photonics platform to realize the overall circuit in one single monolithic chip.

The nonlinear summation provided by our optical output layer scheme, even if expected to be beneficial in terms of computing performances, poses the question of how such a nonlinear summation can be trained. Either black box optimization schemes or algorithms based on accurate simulations of the chips will be required to train the output layer.

Being a first demonstrator, different paths of improvement are still open. For example, while we currently employed traditional attenuator blocks based on thermo-optic Mach-Zehnder interferometers, different ideas are envisioned to improve the heating efficiency and, thus, reduce power consumption, including optical Micro Electro-Mechanical Systems (MEMS),[14] phase change materials,[15] and graphene modulators.[16]

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