Deep neuromorphic computing with optical frequency combs

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Summary. The biological brain is a very efficient computer because it exploits the rich dynamic of the organic substrate. Physical computing consists of processing information by exploiting the dynamic of a specific system, similar to what happens in the brain, without imposing constraints on the information flow, such as logic gates or hard-wired networks. We designed a photonic platform for neuromorphic computing based on frequency multiplexing, where neuron signals are encoded in an optical frequency comb. We demonstrated both feed-forward and recursive neural network algorithms, in particular Extreme Learning Machines and Reservoir Computers. Here we present an overview of our most recent advancements in the field, including achieving parallel computations on the same substrate, fully analog deep Reservoir Computing, and a scheme for an integrated optical and analog output layer.

Artificial neural networks (ANN) are one of the most disruptive technologies of the current century, constituting an exponentially growing research field with massive industrial applications. ANN algorithms process information by propagating it into a brain-inspired network composed of nonlinear activations and weighted connections, tuned to perform specific tasks. The vast majority of these algorithms are based on the actual simulation of the network, mainly performed on electronic digital computers. However, the main reason behind the efficiency of the biological brain is that it directly exploits the physics of the organic material. In view of this fact, simulating a neural network, whether in electronics or in other substrates, appears to be a sub-optimal solution for computation. The biology of the brain teaches us that a specific physical system can be an efficient computer *per se*, without imposing external constraints for information processing and flow, such as hard-coded networks or logic gates. Photonic alternatives to digital electronics have been proposed, but most of them are still aimed at simulating a network: see, for instance, [1].

We developed a platform for photonic neuromorphic computing based on optical frequency combs, meaning that neuron signals are encoded in the amplitude of comb lines. We refer to this concept with the expression "frequency-multiplexed neuromorphic computing". The connectivity among neurons is realized by stimulating frequency-domain interference, which scrambles power across comb lines. This technique does not allow to freely control individual connections, hence the information flow in the network is not trained. In this sense, the system we discuss is conceptually far from being a hard-wired network and closer to being a physical system whose dynamic is directly exploited for computation.

We demonstrated two configurations for frequency multiplexed neuromorphic computing, reported in [2] and [3]. The first configuration is memoryless and can implement feed-forward algorithms, such as Extreme Learning Machine (ELM). The second configuration exhibits memory about past input and can implement recursive algorithms, such as Reservoir Computer (RC).

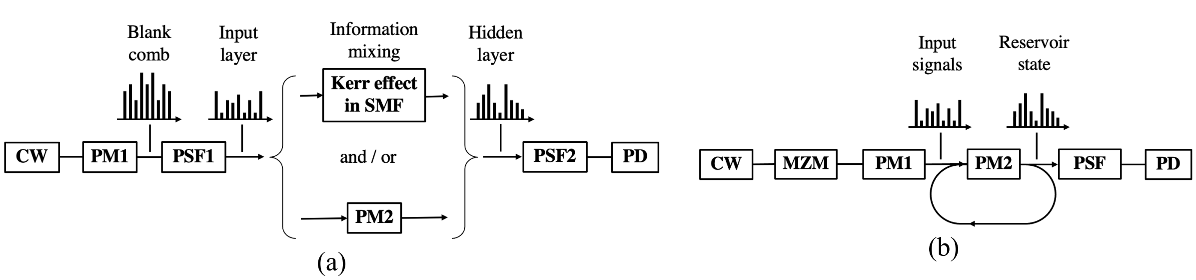

Figure 1. Schemes for the frequency-multiplexed Extreme Learning Machine (a) and Reservoir Computer (b). CW: Continuous-wave laser source; MZM: Mach-Zehnder modulator; PD: photodiode; PM: phase-modulator; PSF: programmable spectral filter; SMF: single-mode fiber. All connections are single-mode and polarization-maintaining. Optical amplifiers are omitted for simplicity.

The memoryless configuration, employed as ELM, is reported in Fig. 1a. The light source is a continuous-wave (CW) laser. The radiation passes through a phase-modulator (PM1) which generates an optical frequency comb. A programmable spectral filter (PSF1) encodes the vector of input data on the frequency comb by attenuating its lines: this constitutes the input layer of the ELM. Input information gets mixed and projected onto a higher-dimensional space by generating frequency interference among lines. Two methods to generate interference have been tested: employing a second phase-modulator (PM2), driven at the same frequency as PM1, or exploiting Kerr nonlinearity in a single-mode optical fiber. The comb after the mixing encodes the hidden layer of the ELM. A second programmable spectral filter (PSF2) applies trained output weights, and a photodiode (PD) records the overall intensity, thus performing a weighted sum of neuron signals and producing the output of the ELM (two PSFs and a balanced PD can be employed to apply both positive and negative weights in the analog domain).

The recursive configuration, employed as RC, is reported in Fig. 1b. The light source is a continuous-wave (CW) laser. A Mach-Zehnder modulator (MZM) modulates the light according to the input time series. The radiation passes through a phase-modulator (PM1) which generates the optical frequency comb. The comb radiation is injected in a fiber loop which contains a second phase-modulator (PM2). PM2 is driven at the same frequency as PM1 and, at each roundtrip, generates interference among comb lines. At each roundtrip, the frequency comb in the loop encodes the state of the RC, which depends both on the current input and on the previous state. A part of the circulating radiation is extracted from the loop and directed to the output layer. A programmable spectral filter (PSF) applies trained output weights, and a photodiode (PD) records the overall intensity, thus performing a weighted sum of neuron signals and producing the output of the RC (two PSFs and a balanced PD can be employed to apply both positive and negative weights in the analog domain).

The versatility of the platform enables us to explore frontier ideas concerning both neuromorphic computing itself and its technical implementation. Recently we demonstrated the possibility of running parallel computations on the same substrate [4]. We also successfully concatenated multiple RCs (still running on the same substrate), in such a way that the output of one RC serves as input for the next one, thus constituting a deep-RC. Deep configurations are proven to enhance the abstraction capabilities of Reservoir Computers [5]. Although photonic deep physical computing has been proposed previously (see, e.g., [6]), our implementation is the first in which the connection among successive layers is fully analog and does not require any digital processing or recording. We experimentally tested the deep-RC performance, recording an improvement of up to two orders of magnitude in the symbol error rate achieved on a benchmark channel equalization task [7] when compared to traditional RC (manuscript currently submitted to Optica). Finally, we recently presented a scheme for an integrated optical output layer that performs a weighted summation of neuron signals, based on the cross-gain modulation of a semiconductor-optical-amplifier (contribution to be published in SPIE Photonics West 2023 conference proceedings, manuscript submitted to Optics Express).

In summary, frequency-multiplexing constitutes a promising platform for physical computing, offering the versatility required to test new ideas in fiber-based implementation and promising high performance in integrated scenarios [8].

References

[1] Y. Shen, et al., “Deep learning with coherent nanophotonic circuits,” Nat. Photonics, 2017.

[2] A. Lupo, L. Butschek, and S. Massar, “Photonic extreme learning machine based on frequency multiplexing”, Optics Express, 2021.

[3] L. Butschek, et al., "Photonic reservoir computer based on frequency multiplexing." Optics Letters, 2022.

[4] A. Lupo, and S. Massar, “Parallel extreme learning machines based on frequency multiplexing”., Applied Sciences, 2022.

[5] C. Gallicchio, et al. "Deep reservoir computing: A critical experimental analysis," Neurocomputing, 2017.

[6] L. G. Wright, et al., "Deep physical neural networks trained with backpropagation." Nature, 2022.

[7] H. Jaeger, and H. Haas. "Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication," Science, 2004.

[8] W. Kassa, et al., "Towards integrated parallel photonic reservoir computing based on frequency multiplexing." Neuro-inspired Photonic Computing, SPIE, 2018.