On-chip photonic neural network for multi-wavelength time-dependent signal processing

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Neuromorphic photonics can greatly benefit processing of optical signals transmitted through telecom links or produced by photonic sensors, by exploiting key advantages w.r.t. electronics such as highly parallel and energy efficient linear operations. We present a compact integrated photonic neural network, composed of 96 neurons (silicon microring resonators) within a 0.15 mm^2 footprint, for high-throughput optical processing concurrently in time, space and frequency domains. We experimentally test it on benchmark image classification tasks, namely MNIST and Fashion-MNIST..

Keywords— Neuromorphic photonics, silicon photonics, physical neural networks, all-optical neurons, reservoir computing.

I. Introduction

A major challenge in neuromorphic photonics is to cascade a large number of photonic artificial neurons, i.e. nonlinear nodes with fan-in capability, which are required to build photonic neural networks [1]. Silicon microring resonators (MRRs) are promising candidates for compact and dynamic photonic integrated neurons, featuring both wavelength-division multiplexing (WDM) and time-division multiplexing capabilities. Thanks to the high sensitivity of MRRs to the absorption and refractive index perturbations due to silicon nolinear effects, these photonic cavities exhibit energy efficient all-optical nonlinearity and even spiking behaviour [2,3]. Hece the growing interest in investigating their employimet in building scalable integrated photonic neural networks (PNNs) [4,5].

In this work, we experimentally study the use of an MRRs-based PNN that supports complex and recurrent dynamics and processes information by leveraging spatial, temporal, and wavelength dimensions simultaneously. Our PNN is notably compact and easy to manufacture. It is composed of 96 MRRs, interconnected by straight waveguides which link to several input and output optical ports (see Fig. 2 a). Owing to the intricate dynamics facilitated by silicon's nonlinear properties and the periodic resonances observed in MRR spectra, the network extends beyond its physical layout into the temporal and wavelength dimensions, while it occupies a minimal on-chip area. We demonstrate that multiple nonlinear representations of the optical input time series (flattened images from the MNIST and the Fashion-MNIST datasets [6,7]) can be simultaneously achieved across various wavelengths. These representations are utilized in an efficient and biologically plausible machine learning (ML) approach, which combines simple linear classifiers, each forming a reservoir computing unit, through ensemble learning [8-10]. Specifically, we reveal that the accuracy in classifying handwritten digits progressively improves with the use of increasing nonlinear representations from our PNN, significantly surpassing the performance achieved with linear representations, thus highlighting the crucial role of our neuromorphic hardware.

Finally, we advance that our PNN can be employed as a versatile *plug-and-play* interface between an optical input comprising several signals at different wavelengths and physical ports (e.g., transmistted thorugh telecom links or generated by a microwave photonics receiver) and conventional electronics-based signal processing, especially machine learning models (Fig. 1). Indeed, our neurmorphic hardware can efficiently produce nonlinear representations of the input signals in real time, enabling: cross-signal interactions accounting for optical phase relationships, multi-scale memory, dimensionality (feature) expansion to enhance the computational power of subsequent machine learning models (e.g. RC applications), addition of on-chip smart sensing information (MRRs can be very effective sensors when their waveguide is exposed to an environment).

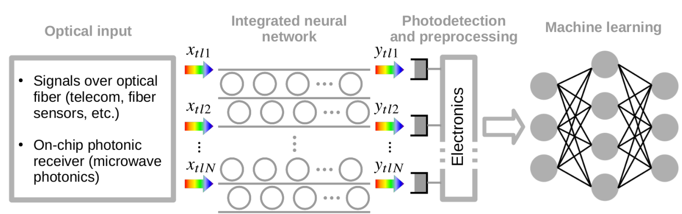

Figure 1: The proposed MRR-based integrated neural network as a plug-and-play neuromorphic interface between optical signal sources and electronics-based processing, to allow for real-time and efficient optical interactions, memory, dimensionality expansion for reservoir computing and addition of on-chip smart sensing information.

II. RESULTS

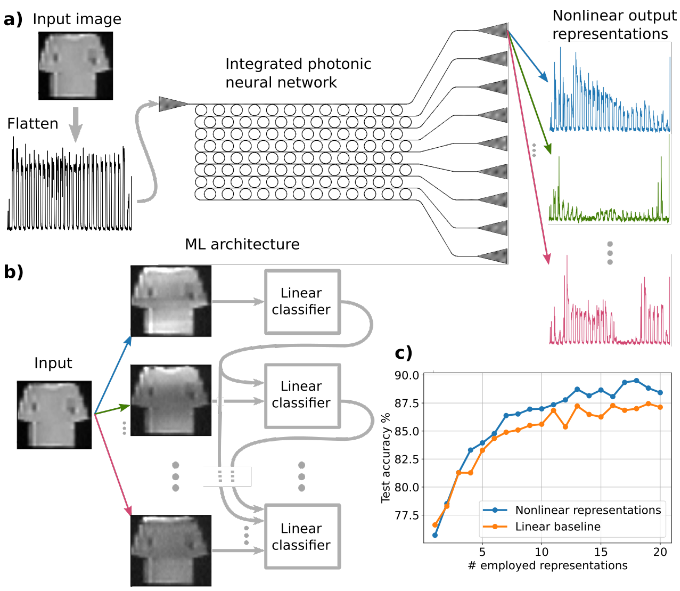

Figure 2: ML image classification enhanced by our PNN. a) Images are flattened into an optical time series without preprocessing and inserted in the PNN. Several nonlinear representations of the input are obtained at different wavelengths and different output ports. b) Diagram of our ML scheme, where linear classifiers applied to different nonlinear representations are hierarchically combined together. c) Accuracy achieved in the Fashion-MNIST classification task as a function of the number of employed nonlinear representations, compared with a linear baseline.

We fed our integrated PNN with flattened images (from MNIST and Fashion-MNIST datasets, 70000 images each) by modulating infrared laser light (wavelengths around 1550 nm, see Fig. 2 a) with a sampling time of 2 ns. We employed 10 different input wavelengths, namely (in nanometers) 1554.46, 1554.62, 1554.78, 1554.94, 1555.10, 1555.26, 1555.42, 1555.59, 1555.75, 1555.91. Additionally, for each input wavelength, 10 distinct optical power levels were employed, each yielding unique nonlinear outputs. Specifically, the estimated on-chip power levels (respectively mean and peak power in milliwatt) were as follows: 0.086, 0.17, 0.26, 0.34, 0.43, 0.51, 0.60, 0.69, 0.77, 0.86, and 1.5, 3.0, 4.5, 6.1, 7.6, 9.1, 10.6, 12.2, 13.7, 15.2. Moreover, we collected data from 5 different physical output ports. Therefore, we acquired a total of 500 different nonlinear representations for each image. In our machine learning analysis, we initially divided the first 60,000 samples from the next 10,000, using them as training and test sets, respectively. Our training procedure combines multiple linear classifier applied to different nonlinear output representations, step by step (Fig. 2 b). Each step aims to incrementally enhance the model's overall performance by learning to rectify mistakes made in previous steps. Further details can be found in [10].

Test ML accuracy was calculated for each training step, each one corresponding to a different number of chosen nonlinear representations (see Fig. 2 c). The classification performance steadily increases with the number of employed nonlinear representations, and it is significantly greater than the linear baseline, which was obtained by the same training procedure applied directly to the input representation (without photonic processing). We reach a maximum test accuracy of 89.5% (with 87.5% linear baseline). Instead, considering the MNIST classification task, we achieved a test accuracy of 94.5% (with 92% linear baseline).

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III. CONCLUSIONS

We experimentally demonstrated the use of an integrated photonic neural network based on silicon microring resonators for hardware-based machine learning, applied to images flattened into optical time series, without any preprocessing. In particular, we tackled the MNIST and Fashon-MNIST image classification tasks, obtaining a test accuracy of 94.5% and 89.5% respectively, via a combination of reservoir computing units. In both cases, we observed a significant improvement w.r.t. the linear baseline, thus demonstrating the enhancement of ML performance obtainable with simple and computationally cheap linear classifiers.

Our network comprises 96 nonlinear nodes with volatile memory within a small footprint, and can produce hundreds different nonlinear representations of its input, via highly parallel and energy efficient operations in the spatial, temporal and frequency domains. Finally, our photonic neural network can be employed as a versatile neuromorphic interface between optical signal sources and electronics-based processors to enhance machine learning performances while enabling new functionalities.

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