Performance enhancement via synaptic plasticity in an integrated photonic recurrent neural network with phase-change materials

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Synaptic plasticity, i.e. the ability of synaptic connections to strengthen or weaken depending on their input, is a fundamental component of learning and memory in biological neural networks [1]. This property allows the network parameters to directly adapt to the input signal, thus without being externally tuned by a training algorithm. In contrast with this paradigm, the most popular and successful artificial neural network (ANN) models are nowadays based on backpropagation, which usually requires full observability of the network states and precise parameter tuning. In practice, these requirements strongly limit the scalability of neuromorphic hardware and backpropagation is not considered biologically plausible [2].

We present a novel all-optical recurrent ANN which can adapt to its input via synaptic plasticity. The platform is integrated silicon photonics and plasticity is obtained through deposition of phase change material (namely GST [3]). We experimentally demonstrate the network employment as a plastic reservoir for reservoir computing (RC), where the performance on a time series classification task is enhanced by letting the photonic network adapt to suitable input waveforms. Our network consists of several coupled silicon ring resonators (RRs). One every three RRs is partially covered with GST and is used as plastic node with all-optical non-volatile memory [4]. Moreover, the RRs without GST are employed as nonlinear neurons with multi-scale volatile memory, arising from the silicon nonlinear effects in the ring waveguide [5,6].

In our experiment, we tackled the classification of 5 time series types, inserted as optical waveforms in our RR network (Fig. 1(a)). The reservoir network generated several different nonlinear representations of the input waveform, thus expanding the input dimensionality. Each output waveform was integrated over time, allowing to employ slow electronics. The obtained waveform energies were fed into the reservoir readout (linear classifier trained by logistic regression). The classification performance was repeatedly evaluated via 6-fold cross-validation (Fig. 1(b)). Between each evaluation, we performed a plastic adaptation step, consisting of the repeated insertion of a modified version of an input waveform class (a different class for each step). Each modified waveform type could permanently change the configuration of the plastic weights (GST cells) in a different way. We show (Fig. 1(b)) that the plastic adaptation steps could significantly improve the classification performance, allowing to decrease the error from more than 40% to less than 10%. A similar trend was observed for other input wavelengths.

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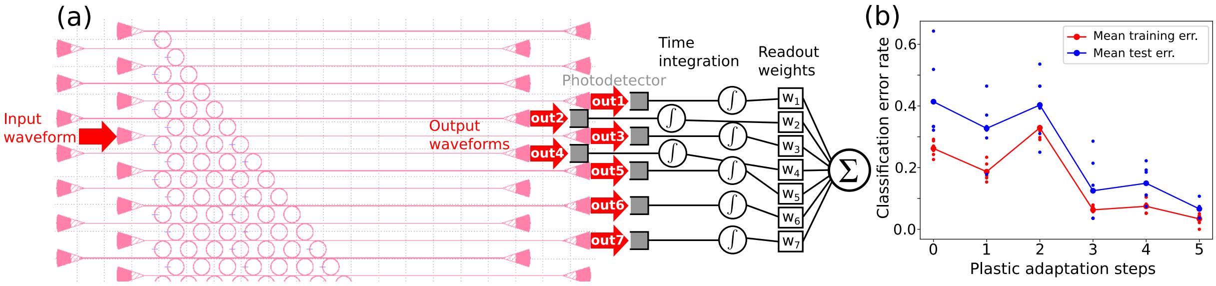

Fig. 1 (a) Schematic of our machine learning inference pipeline: the output waveforms from our photonic reservoir network are acquired by photodetectors and integrated over time, before being fed into a linear classifier. (b) Corresponding classification error rate after different plastic adaptation steps.

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