Optical Computing in Silicon Photonics: Self-Adapting Ring Networks and Quantum Recurrent Neural Networks

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Summary. We will present two different incarnations of silicon photonics for information processing. The first one is a network of ring resonators with patches of phase change materials, which experimentally shows synaptic plasticity. The second one is a recurrent quantum neural network that is trained to perform a quantum version of optical channel equalisation. We present simulations of a silicon quantum photonics network, and will supplement this with experimental results on the Xanadu Borealis fibre setup.

Self-adapting ring networks

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.

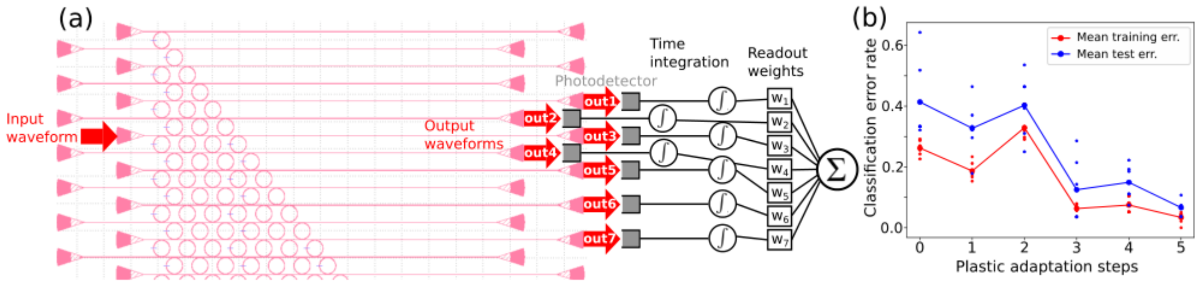

Figure. 1 (a) Outputs are detected and integrated over time, before being fed into a linear classifier. (b) Classification error rate after different plastic adaptation steps.

Quantum recurrent neural networks

We also have been investigating the reservoir computing paradigm in the context of online quantum time series processing. More specifically, this means looking at tasks where both the input and the output are quantum states. This is in contrast to most other work in the field of quantum reservoir computing, which considers tasks with a classical output. In the case of classical output, the reservoir observables are typically expectation values, and therefore the system needs to be run multiple times in order to estimate these expectation values. This results in a slow, unpractical experimental system that cannot perform online (i.e. real-time) processing of an incoming datastream. The task we have been studying is the quantum channel equalisation (QCE) task: given the output of a quantum channel with memory, which imposes correlations and entanglement on an input stream, train a system to undo these effects and generate an unentangled output stream. Fig. 2 visualises a setup that can be used to tackle the QCE task: a decoder is trained to undo the effects of a randomly chosen encoder. We will present experimental results on the Xanadu Borealis setup that illustrate this task.

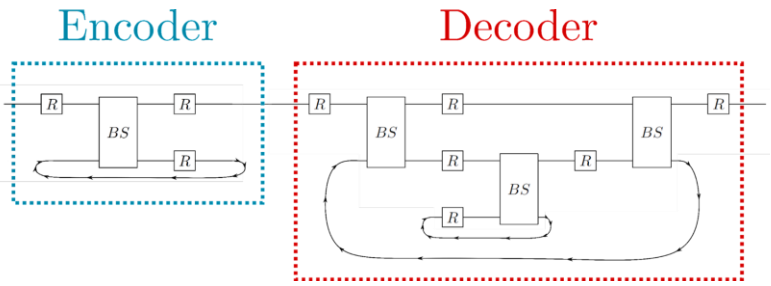

Figure 2: Setup to solve the QCE task.

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