Phase Noise Robustness of a Spatially Parallel Optical Reservoir Computer

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We present numerical results on a spatially parallel photonic reservoir computer based on a linear Fabry- Pérot cavity with diffractive coupling between 81 neurons and a nonlinear readout operating at 0.5GHz. We characterize the reservoir's robustness to both slow and fast phase variations and propose practically feasible improvements to the system.

Introduction to optical reservoir computing

When solving difficult tasks such as spoken digit classification or face recognition, algorithmic approaches often struggle. Yet our brain manages to overcome these challenges quickly and with great power efficiency. A special branch of neuromorphic or brain-inspired computing is known as reservoir computing (RC) [1,2]. This computing paradigm offers a framework to exploit the transient dynamics of a recurrent nonlinear dynamical system for performing useful computations. In the schematic example in Fig. 1, input data is coupled to an interconnected pool of dynamical nodes or neurons. What makes reservoir computing suitable for hardware implementation is the simplicity of the training procedure, compared to other neuromorphic computing schemes. The strengths of the input connections and internal connections are kept fixed, and only the output connections are optimized during training. The diversity of neural responses, each representing a complex nonlinear transformation of the input data, provides the reservoir with exceptional computational capacity.

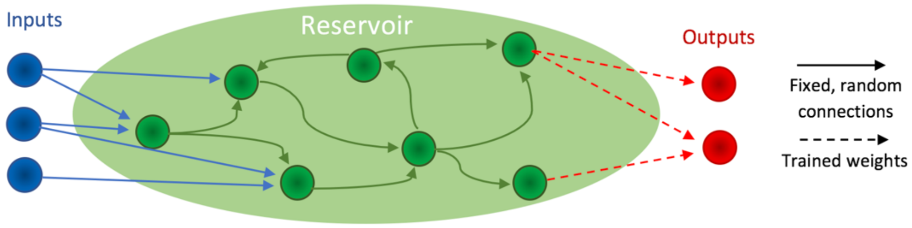

Figure 1. Schematic of a reservoir computer

With the promise of massive parallelism and high available bandwidth, the field of photonics offers a great platform for implementing these neuromorphic computers. Over the past few years, several photonic reservoir computers have been reported [3-10]. In this paper, we report on a system that uses a linear optical reservoir, with nonlinearity implemented in the output layer by the readout photodiode. A linear photonic reservoir with nonlinear readout has been reported [10], but was limited in terms of scalability and parallelism. Our setup is built to exploit the advantages of the optical domain in order to improve scalability over previous photonic reservoir computers. At the core of our high bandwidth photonic RC implementation lies a linear Fabry-Pérot cavity, see Fig. 2.

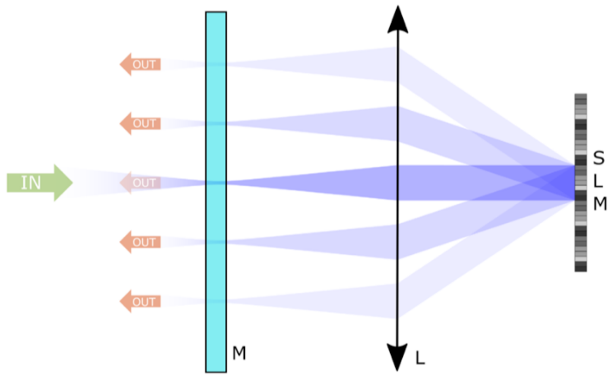

Figure 2. Schematic of the Fabry-Perot based reservoir computer which encodes neurons in the transverse spatial extent of the input coupler (M), and couples them together using an intracavity lens (L) and a diffractive optical element at the cavity backend, implemented using a phase-only spatial light modulator (SLM)

Although the reservoir itself is linear, a nonlinearity is found in the readout layer where a photodiode measure the optical power of each neuron. This cavity is essentially the reservoir, and the neurons are found on the cavity's input coupler. This reservoir was designed to process input samples at a rate of 0.5GHz. Data is coupled to the reservoir by focusing a modulated light beam on the cavity input coupler. A lens is placed in the resonator center, with its conjugal planes on either ends of the cavity. At the cavity backend, the cavity coupler is replaced by a reflective diffractive optical element (DOE), implemented using a phase-only spatial light modulator (SLM). The injected light beam is first collimated by the intracavity lens and then diffracted by the SLM. Each diffraction order is again focused onto a spot on the input coupler. The optical fields at the locations of these spots represent the neuron states. These neuron states are mostly reflected within the cavity and will couple to even more neurons during the next cavity roundtrip. As such, a grid of neurons is created in the 2 dimensional transverse spatial extent of the cavity input coupler. The system was designed to support up to 9x9 neurons. The part of the neuron states that escapes the cavity is sent to the readout photodiode. The diversity in the neural responses stems from the fact that many different multi-roundtrip paths exist within the optical cavity, thus resulting in spatial and temporal mixing of the injected data.

Diffractive reservoir: numerical methods

We are currently looking at two ways to numerically simulate the reservoir. A first approach is to model propagation the optical fields between the extreme ends of the cavity, taking into account the intracavity lens and diffraction for each roundtrip. This robust approach allows to take into account geometrical effects such as defocusing. A second approach is to track how 1 neuron is diffractively coupled to all others over just 1 roundtrip. The resulting neural responses can be reformatted into a matrix which yields a per-roundtrip update equation much like the standard matrix formalism used in (software) RC. This equation takes into account the cavity detuning and the spatial mixing between neurons caused by the diffractive coupling at the cavity backend.

Phase noise robustness

Currently our numerical investigations focus on the effect of both slow and fast temporal variations of the cavity detuning, as it may be expected to change when the reservoir is in operation, or even during the training procedure. To benchmark the performance, we train the reservoir to reconstruct a nonlinearly distorted quaternary signal. This task emulates the problem of multi-path reflection in a fast telecommunication scheme. The reservoir has to process the distorted input and recover the original signal by correctly classifying each sample. When the detuning is constant during the whole experiment, the reservoir can perform the task with more than 99% accuracy, which is equivalent to making only a few mistakes over ten thousand samples. But a small difference of detuning between the time of training and time of operation drastically degrades the RC performance down to that of a random classifier when the difference reaches only 0.1% of 2π. To quantify this dependence, we train the reservoir on a fixed detuning value and test its performance when the detuning has changed to a different fixed value. We find that the readout weights obtained during training can be used to produce useful reservoir output during testing, albeit with a degradation of performance which grows rapidly with the variation of detuning. This performance drop is in large part due to a shift in the (unfiltered : UF) reservoir output and can be explained by changes in the average optical power per neurons. In practice, this kind of problem can happen if there is a slow variation of the detuning during the experiment because the network would be trained with a single-phase value (SP) and operated at another one. But there are two ways to compensate this shift as the Figure 1 shows: It can either be corrected by a suitable high-pass filter (F) or anticipated by training the network with a multitude of phase values $S = \{\phi_1, \phi_2, \dots\}$.The Multi-Phase (MP) training considerably improves the RC phase noise resistance when testing with a detuning value inside or even slightly outside the range of values in S, but the best phase noise robustness is obtained when both methods are combined.

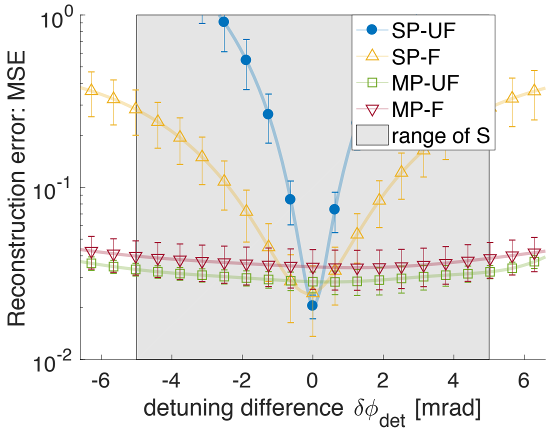

Figure 3. Simulated mean squared error (MSE) on 4-level channel equalization task, for single-phase (SP) and multi-phase (MP) training, with filtered (F) and unfiltered (UF) reservoir output.

When the detuning is expected to vary quickly enough to change its value during the experiment, we can no longer keep the detuning fixed during training or testing parts. If we do not consider the slow variations, then the magnitude and the bandwidth of this fast phase noise would be the same during both training and operation. In this case, the neural network will naturally be robust to a certain degree. But if we want to make the system robust for a longer time, then we must train the network with bigger noise variations to anticipate the shift during operation. However, generating large random phase variations is practically difficult. Alternatively, we find that training with phase ramps gives even better results and is practically easier to implement. Even so, Figure 3 shows that the network corrects the phase noise more efficiently if it varies in the same range during operation as it did in the training part.

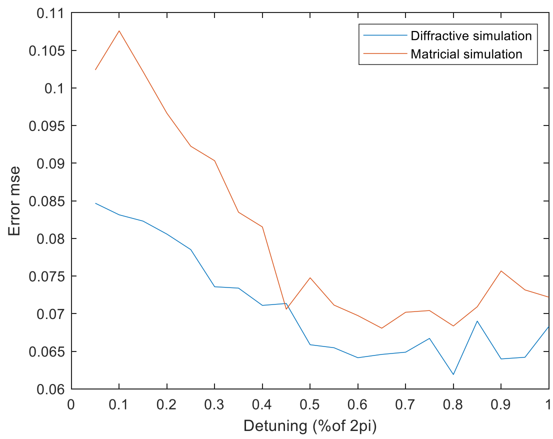

Figure 4. Simulated mean squared error (MSE) on 4-level channel equalization task, for a detuning noise amplitude of the testing part varying from 0 to the detuning noise amplitude of the training part, which is 2pi in this case.

Conclusion

We presented numerical results on the phase noise robustness of our high bandwidth photonic reservoir computer with parallel encoding of the neurons. The expected fast temporal variations of the cavity detuning can be mitigated by the reservoir's inherent noise robustness. Slower variations cause more problems during prolonged operation and force us to compromise between the duration of the window of operation and the efficiency of the noise correction.

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