Wavelength Multiplexing in Photonic Reservoir Computing

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Abstract

Existing work on coherent photonic reservoir computing mostly concentrates on single-wavelength solutions. In this work, we discuss the opportunities and challenges related to exploiting the wavelength dimension in integrated photonic reservoir computing systems. We will focus on multi-node waveguide-based integrated RC systems developed on a silicon photonics platform. These systems have been shown to perform well in our previous work but suffer from a large footprint which limits economic viability.

Different strategies are presented to be able to process several wavelengths in parallel using the same readout. This increases the system bandwidth without increasing the footprint. It is shown that a single-readout photonic reservoir system can perform with < 1% BER for bit-level tasks on several WDM channels in parallel, even when taking manufacturing deviations. This clears the way toward commercial viability of photonic RC systems as the same chip footprint now has significantly increased processing power and reliability.

Introduction

Reservoir computing (RC) employs a randomly initialized fixed recurrent neural network (RNN), called the reservoir, which is left untrained and to which a simple linear readout layer is added. Only this linear readout is trained, greatly facilitating the practical application of RNN's [1–3]. RNN's differ from feedforward neural networks by preserving in their internal states a nonlinear transformation of the input history. Thus they have dynamical memory, which makes them suited to process temporal information.

Photonics-based hardware implementations have an additional set of advantages. In particular, low power consumption and high data bandwidth make photonics-based hardware implementations attractive choices. In addition, exploiting wavelength division multiplexing enables parallelism. We will focus on multi-node waveguide-based integrated RC systems developed on a silicon photonics platform. We focus on making more efficient use of a given chip area by exploiting wavelength-division multiplexing (WDM).

The different nodes of the reservoir are weighted in the analog optical domain for both amplitude and phase. We use a single set of optical weights for all wavelengths to maximize all the chip area savings. This can only be achieved in cases where a single task has to be executed for several wavelength channels in parallel. The simulated reservoir is an integrated passive silicon photonics reservoir based on the designs outlined in [4–6] (figure 1). The nodes consist of 3x3 multimode interferometers (MMIs). All nodes are connected to readout weights consisting of both amplitude and phase weights. A 17th amplitude-phase weight set was connected to a continuous-wave optical signal serving as a trainable optical bias. The simulations are done in Photontorch [7], a set of photonic simulation tools for simulation and optimization of photonic circuits in time and frequency domain.

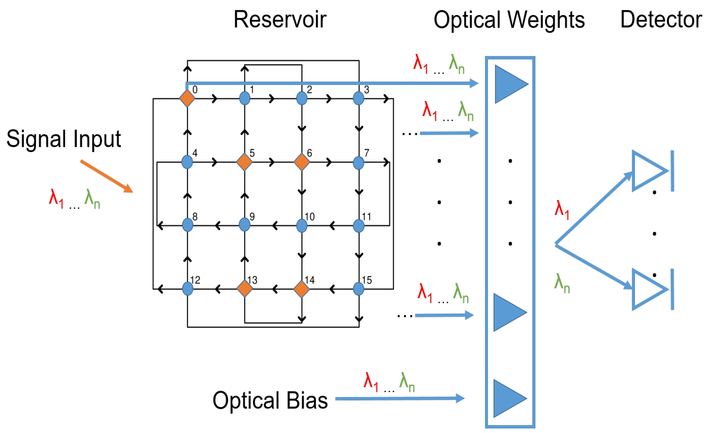


Fig. 1. Schematic of the simulated system. Signal input in injected in the orange diamond shaped nodes. All nodes are connected to the readout. Arrows indicate propagation direction of the signal throughout the reservoir.

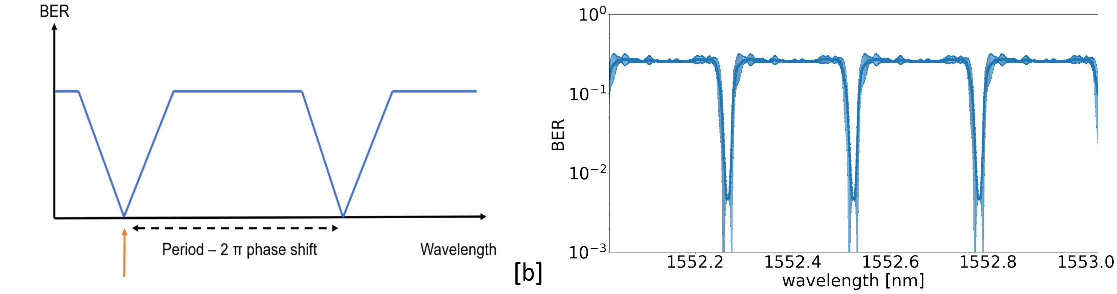
Engineered Interconnection Lengths

When all interconnections are of identical length, there will be frequency changes for which the corresponding phase shift variation equals an integer multiple of 2π. The frequency change inducing a 2π phase shift is approximately constant, with variation being caused by dispersion. This gives rise to approximate frequency periodicity in reservoir performance (figure 2a). By engineering the waveguide interconnection length, one can ensure that the frequency spacing between DWDM or CWDM channels corresponds to this period.

An important boundary condition is that the interconnection length should not surpass the distance that light can travel during a single bit period (d_{max}). This causes previously injected bits to be in transit in between nodes, hidden from the readout. There is thus an upper limit imposed on the interconnection length. This in turn imposes a lower limit on the frequency periodicity. For the bitrate B of 32 GHz, employed throughout this paper, the maximum interconnection length $d_{max} \approx 2$ mm and the minimum frequency periodicity ≈ 32 GHz corresponding to a wavelength shift ≈ 0.257 nm around 1552.5244 nm.

We test this method using a nonlinear bit-level task, namely the delayed 2-bit XOR task. This task consists of performing the Boolean XOR operation using the current and previous bit. The readout weights are trained on a training bit stream of 1000 bits using ridge regression.

To account for manufacturing variations interconnection phases need to be considered random and the interconnection length variations are normally distributed with mean 0 nm and standard deviation 21.08 nm. 10 different reservoirs, each with different manufacturing deviations, were trained and tested. Results, using the minimum periodicity of 32 GHz, are shown in figure 2b. At 1552.5244 nm, and the wavelengths separated from it by the period, a BER ≈ 0.3% is achieved for all reservoirs.

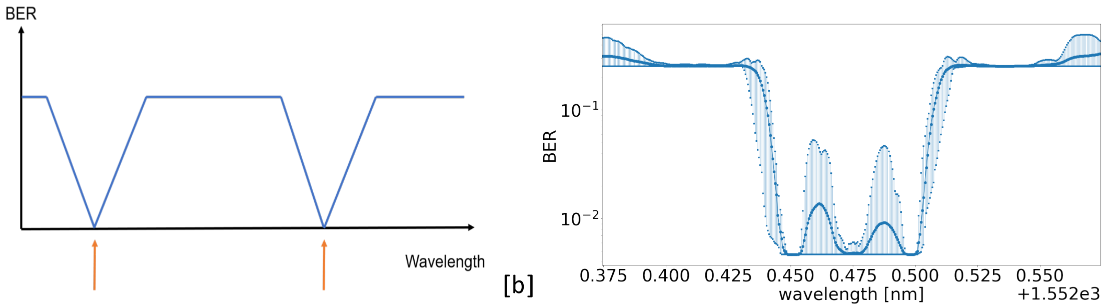


[a]

Fig. 2. Exploiting engineered interconnection length. (a) Training only occurred for one wavelength (1552.5244 nm), as indicated by the orange arrow. (b) Performance for the delayed 2-bit XOR task. Error bars indicate minimum and maximum achieved BER over 10 different reservoirs each with their own manufacturing deviations.

Multiple-Wavelength Training

Another method consists of minimizing the MSE for multiple frequency channels simultaneously (figure 3a). Here there are no boundary conditions on frequency spacing.



[a]

Fig. 3. Multiple-wavelength training. (a) Training occurred at 2 wavelengths as indicated by the orange arrows. In this case, we used 1552.4489 nm and 1552.4994 nm. (b) Performance for the delayed 2-bit XOR task. Wavelength channels achieve approximately 0.4% mean BER. Error bars indicate minimum and maximum achieved BER for different reservoirs with their own simulated manufacturing deviations.

Conclusion

We demonstrated that a single-readout photonic RC system can perform with < 1% BER at several wavelength channels for the delayed 2-bit XOR task. This was done while taking into account manufacturing deviations.

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