Time Series Prediction and Classification using Silicon Photonic Neuron with a Self-Connection

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Abstract: We experimentally demonstrated real-time operation of a photonic neuron with a self-connection, a pre-requisite for integrated recurrent neural networks (RNNs). After studying two applications we propose a photonics-assisted platform for time series prediction and classification.

1. Introduction

Silicon photonic neural networks have been proposed for various applications including image classification, solving differential equations, and fiber nonlinearity compensation [1, 2]. However, most networks were not suitable for performing temporal correlations in time series signals. In this work, we exploit the self-connection dynamics of an integrated neuron to amplify short-term correlations while processing temporal data. In the following sections, we show the behavior of a single neuron with a feedback self-connection as a demonstration of the simplest recurrent neural network. Despite its simplicity, we show that it is capable of performing well in two distinct classes of time-series processing: a prediction task called NARMA-10, and a binary classification task based on the Ford-A dataset [3].

2. Device and Experimental Setup

A photonic recurrent neural network is designed as shown in Fig. 1. It consists of a microring weight bank (MWB), a balanced photodetector (BPD), and a microring modulator whose output is connected back to the input of MWB. This neuron circuit was fabricated on a silicon photonic integrated platform with high-speed optical I/O ports connected to optical fibers and low-speed electrical ports connected to electrical sources. The electrical sources are used to bias the MWB, BPD and Modulator devices. In this experiment, we focus on observing the behavior of one neuron as a function of the input coupling weight (w_{ih}) and feedback weight (w_{hh}).

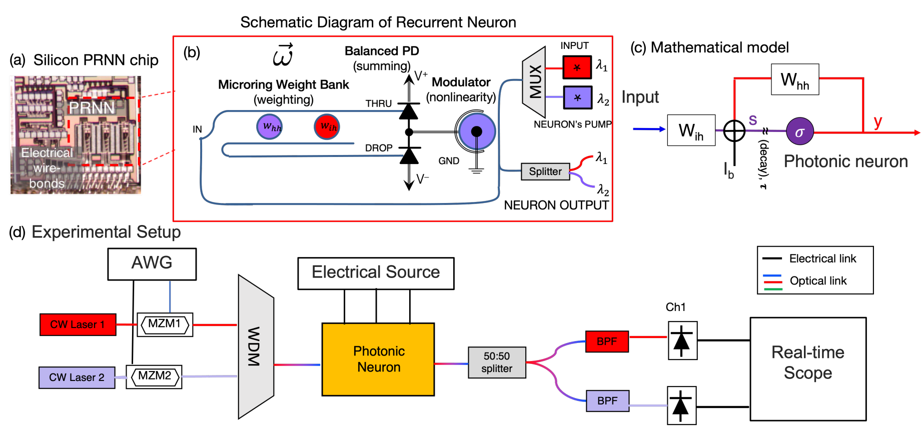

Fig. 1: (a) Micrograph of silicon photonic chip (b) Schematic diagram of the integrated photonic neuron. (c) Mathematical model of the neuron and its self-connection. (d) Experimental setup diagram for real-time testing; Laser 1 in red carries the input signal, and laser 2 in purple carries the optical input to the on-chip microring modulator.

3. Results

The proposed photonic recurrent neural network can be used in two approaches, namely as a single node time delayed reservoir or a dynamical RNN emulator. We have applied both approaches with known machine learning tasks, NARMA-10 and Ford-A.

3.1. *Time Delayed Reservoir – NARMA-10*

The photonic neuron with delayed self-connection can be considered a single node time delayed reservoir system as shown in Fig. 2 (a). We perform NARMA-10 prediction using the same framework as in Ref. [4]. An input weight mask consisting of 100 random values are multiplied to each input value of the NARMA-10 series. Here, the weighted input was programmed by arbitrary waveform generator and modulated to optical domain using a Mach-Zehnder Modulator (MZM1 on Fig. 1 (d)). We configured the feedback weight value to be $w_{hh} = 1$ to maximize nonlinear feedback dynamics, and measured the output of the silicon recurrent neuron (Fig. 2 (b)). Based on the output time series, the weights were then trained to match the NARMA-10 output sequence by ridge regression offline. Our results show a normalized root mean square error (NRMSE) of 0.15, compared to 0.18 from Ref. [4].

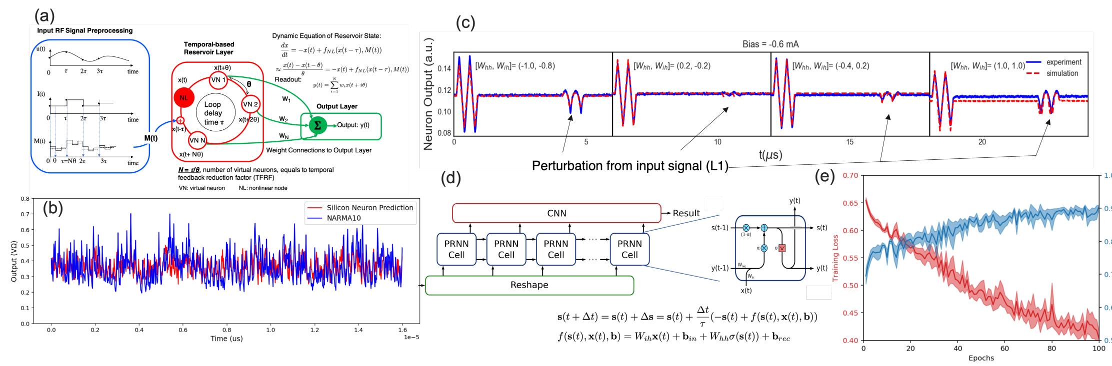

Fig. 2: (a) The schematic diagram of a time delayed single recurrent neuron. (b) Output waveform after training for NARMA-10. (c) Experimental validation of photonic recurrent neuron dynamical model. (d) Neural network architecture schematics for time series classification based on the validated neuron model (same framework as in Ref. [6]). (e) Training loss while learning with the Ford-A dataset.

3.2. *Dynamical Model – Ford A Classification*

We constructed and experimentally verified a dynamical model of the photonic recurrent neuron, given in Eq. 1.

$$\frac{d\vec{s}}{dt} = \frac{-\vec{s}}{\tau} + \mathbf{W_{hh}}\vec{y}(t) + \mathbf{W_{ih}}\vec{x}(t) + \vec{b}, \quad \vec{y}(t) = \sigma(\vec{s}(t)), \tag{1}$$

where $\vec{s}$ is the neuron's state (current injected to the modulator); $\vec{y}$, the output optical signal; $\vec{x}$, the input signal; τ, the time constant of the photonic circuit; $\mathbf{W_{hh}}$, feedback weight; $\mathbf{W_{ih}}$, the input coupling weight; $\vec{b}$, the modulator bias; and $\sigma(\cdot)$, the transfer function of the modulator (Lorentzian-shaped [5]). We verified the model with a single recurrent neuron experiment, where we fixed the neuron's bias at -0.6 mA. We then programmed one triangle wave followed by a constant value to neuron's pump signal. The input signal carried another triangle wave at a later time to perturb neuron's constant internal state. The model simulation matches with experimental results at different weight configurations (Fig. 2 (c)). We use the dynamical model and a CNN with the framework proposed by Peng *et al.*(Fig. 2 (d) [6]) to perform a task involving detecting anomalies in a vehicle's engine (Ford A). The combination of photonic recurrent neural network and CNN model can successfully classify Ford A test dataset with 92.2% (Fig. 2 (e)).

4. Conclusion

This work performs signal processing directly after the signal acquisition before any analog-to-digital conversion. A silicon photonic neuron can have a much lower latency than electronic systems. We showed it can can detect temporal correlations and extract features from complex time series (NARMA-10 and Ford-A) in real time, and can be expanded to applications requiring high-bandwidth (GHz) input signals where a hard deadline between problem detection and reaction is necessary.

References

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