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

Hsuan-Tung Peng[1,2], Thomas Ferreira de Lima[1,2], Eric C. Blow[1], Simon Bilodeau[1], Aashu Jha[1], Chaoran Huang[1,3], Bhavin J. Shastri[1,4], and Paul R. Prucnal[1]

[1]*Department of Electrical and Computer Engineering, Princeton University, Princeton NJ, 08544 USA*
[2]*NEC Laboratories America, Princeton NJ, 08540 USA*
[3]*Department of Electrical Engineering, The Chinese University of Hong Kong, Hong Kong, China*
[4]*Department of Physics, Engineering Physics & Astronomy, Queen's University, Kingston, ON K7L 3N6, Canada*

hpeng@princeton.edu, thomas@nec-labs.com

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(wn)-3-34