

Compact Design of On-chip Elman Optical Recurrent Neural Network

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Abstract: We propose an on-chip optical Elman recurrent neuron network (RNN) architecture for high-speed sequence processing using Mach-Zehnder interferometers and looped waveguides. The proposed design paves way for future integrated-photonics-based artificial intelligence hardware design. © 2020 The Author(s)

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1. Introduction

Artificial neural network (ANN) is developing rapidly and is shaping our lives. Photonic computing has been rekindled as promising for implementing machine learning tasks due to high transmission speed, low power consumption, and advantages in matrix computing compared with electronic architectures [1]. Among ANN architectures, recurrent neuron network (RNN) is specialized in time sequence processing, like speech recognition and sequence prediction.

Using delay systems to realize RNN with integrated photonic circuits is popular in recent studies [2]. Most studies focus on reservoir computing [3], the models of which are not similar to RNN models studied in computer science. As a result, they are not compatible with current training methods in the traditional machine learning area when the model complexity increases.

In this paper, we propose a novel and compact on-chip photonics architecture realizing the classical Elman RNN model, which is well studied in computer science. The mechanism of our architecture is illustrated first and then verified via simulations, which reveals that our architecture is capable of handling problems related to sequence processing. Analysis of the performance as well as the robustness of our architecture will be carried out in the future.

2. Theory and design

Elman RNN defines the following behavior:

$$\mathbf{h}(t) = \sigma_1(\mathbf{W}_{hh}\mathbf{h}(t-1) + \mathbf{W}_{hx}\mathbf{x}(t) + \mathbf{b}_o) \quad (1)$$

$$\mathbf{o}(t) = \sigma_2(\mathbf{W}_{ho}\mathbf{h}(t)). \quad (2)$$

where the hidden state $\mathbf{h}(t)$ is defined by its previous state ($t-1$) and input signal $\mathbf{x}(t)$. \mathbf{W}_{hx} , \mathbf{W}_{hh} , \mathbf{W}_{ho} are real matrices while σ_1 , σ_2 are non-linear activation functions. A great challenge for building optical RNN is that few on-chip silicon photonics devices can memorize. While using electronics components to realize the recurrent relation will slow down the calculation and cause excessive energy consumption.

The schematic architecture of our optical RNN (ORNN) is shown in figure 1, where a 2×2 photonics RNN architecture and its $n \times n$ extension are shown. The mechanism of our architecture is shown as follows: The inputs of ORNN $\mathbf{x}(t)$ are connected to an MZI array that can implement any real matrix [1] denoted as \mathbf{W}_1 producing $\mathbf{x}'(t)$. $\mathbf{x}'(t)$ will interfere with \mathbf{g} via a 50/50 directional coupler, producing $\mathbf{h}(t)$. Then light $\mathbf{h}(t)$ will propagate through the second matrix array that can implement matrix \mathbf{W}_2 and then be looped back, producing \mathbf{g} to interfere with $\mathbf{x}(t)$ in the directional coupler. Finally, some portion of $\mathbf{h}(t)$ will be coupled out. The coupled light will pass through a non-linear activation block σ , producing outputs $\mathbf{o}(t)$. The transfer functions can be simplified as:

$$\mathbf{h}(t) = (\mathbf{W}_{hh}\mathbf{h}(t - \tau - \tau_1)e^{-i\phi - \pi/2} + \mathbf{W}_{hx}\mathbf{x}(t - \tau_1))e^{-i\phi_1} \quad (3)$$

$$\mathbf{o}(t) = \sigma(\mathbf{W}_{ho}\mathbf{h}(t)). \quad (4)$$

$$\mathbf{W}_{hh} = (\sqrt{2}/2)\mathbf{W}_2; \mathbf{W}_{hx} = (\sqrt{2}/2)r\mathbf{W}_1; \mathbf{W}_{ho} = ik \quad (5)$$

where τ_1 and ϕ_1 are the signal transmission time and phase change through the MZI array \mathbf{W}_1 while τ and ϕ are the signal transmission time and phase delay through \mathbf{W}_2 as well as the feedback loop. By selecting appropriate waveguide length, we let $\phi = \frac{\pi}{2} + \phi_1 + 2m\pi$, m is an integer. Other phase changes that will not result in intensity

changes of $\mathbf{o}(t)$ are not mentioned for simplicity. k is the coupling coefficient between the waveguides carrying signals $\mathbf{h}(t)$ and $\mathbf{o}(t)$, while r is the transmission coefficient.

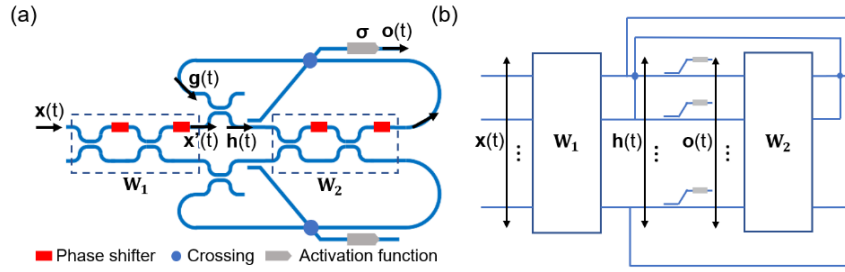


Figure 1: (a) Schematic structure of a 2*2 photonic RNN and (b) n*n photonic RNN.

Comparing the field intensity of $\mathbf{h}(t)$ and $\mathbf{o}(t)$ in Eq. (3, 4) with Eq. (1, 2), one can find the transfer function of our architecture is similar to Elman RNN architecture except that σ_1 is not used to reduce the number of non-linear optical devices. Therefore, our proposed structure can be trained with well-developed training methods.

3. Simulation result

We train the proposed ORNN architecture in PyTorch framework based on Eq. (3-5) and verify our model using Lumerical Interconnect, where the parameters of optical components are set based on previous literatures and process design kit (PDK) models of silicon photonics foundries [4]. The bit rate of the signal is 100 Gb/s. Amplifiers are deployed in the feedback loop to compensate for propagation loss of directional couplers and waveguides. The activation functions of ORNN can be realized by saturable absorbers or electrooptic modulators in previous literatures [5]. Here, we build an ORNN with two inputs, which is similar to the structure in Fig. 1(a).

The training results are shown in Fig. 2. Figure 2(a) measures the step response of the ORNN where W_{hh} and W_{hx} are identical matrices, which reveals that our model matches well with Lumerical Interconnect, a reliable commercial software. Fig. 2(b) and 2(c) show a proof-of-concept application of a sequential binary adder. Note that in the simulation results, the least significant bit (LSB) comes first. The converted decimal sums match well with the correct results. More training results and applications of our ORNN will be shown in the presentation.

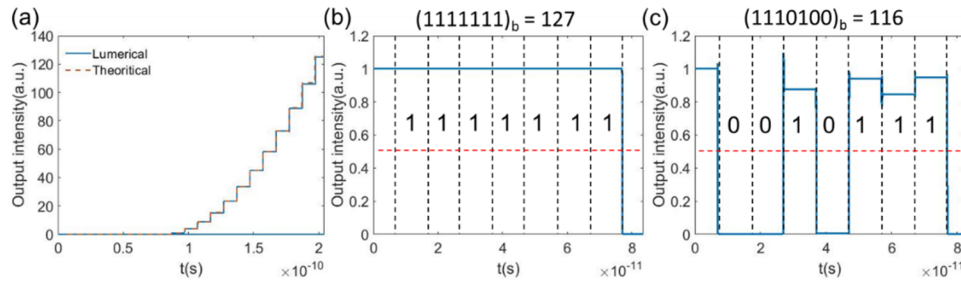


Figure 2 Trained waveforms of optical RNNs (a) step response (b) Sequential full adder results ($89+38=127$) (c) Sequential full adder results ($52+64=116$). Both (b) (c) are simulated on Lumerical Interconnect.

In conclusion, we have proposed a compact architecture of Elman recurrent neuron networks and test its performance with Lumerical Interconnect. Our architecture outperforms electronics counterparts in speed and energy consumption. Besides, the architecture is compatible with current machine learning training methodologies. This study paves the way for future large-scale deep learning and neural computing on photonics chips.

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