Experimental Implementation of An All-Optical Reservoir Computer Using Photonic Time Stretch and Spectral Mixing

Yuanli Yue
School of Engineering
University of Kent
Canterbury, United Kingdom
yy282@kent.ac.uk

Shouju Liu
School of Engineering
University of Kent
Canterbury, United Kingdom
ls777@kent.ac.uk

Yanrong Zhai
School of Engineering
University of Kent
Canterbury, United Kingdom
School of Communication and Engineering
Hangzhou Dianzi University
Hangzhou, China
y.zhai@kent.ac.uk

Chao Wang
School of Engineering
University of Kent
Canterbury, United Kingdom
c.wang@kent.ac.uk
ORCID: 0000-0002-0454-8079

***Abstract*—Reservoir computing (RC) has been widely used in processing temporal information and classification tasks due to its high efficiency in training and testing. In this paper, we have experimentally demonstrated the performance of an all-optical reservoir computer based on time stretch and spectral mixing. Spectral comb lines of the stretched optical pulse are chosen as virtual nodes in the reservoir layer. Nonlinear spectral mixing is achieved through phase modulation and semiconductor optical amplification. A simple temporal waveform classification task was implemented using the demonstrated RC system to verify the approach.**

Keywords—reservoir computing, photonic time stretch, dispersion, spectral mixing, classification

I. Introduction

In recent years, with the ever-increasing demand for efficient information processing, machine learning, especially Deep Neural Networks (DNNs), has provided a promising solution to address a wide variety of problems. However, this powerful tool has caused a relatively high computational cost in training and application [1,2].

Among various types of DNNs, Reservoir Computing (RC), a special variant of Recurrent Neural Networks (RNN), has emerged in the last decade as an alternative to gradient descent methods for training RNN [3]. RC is introduced and simplified the training of RNN by only training the output weights. Therefore, such an approach is computationally fasters and consumes less energy.

Photonic hardware implementation of reservoir computer, with great potential of low power consumption and extremely fast computation, was first proposed in [4]. The performance of RC system is determined by the rich dynamics in the reservoir layer. The number of nodes in the reservoir layer has a significant influence on the performance of RC. Great research efforts have been made to improve the number of nodes to enhance the prediction/classification performance [5].

There are mainly two ways to achieve a large number of nodes in the reservoir layer: optical node arrays, and time-delay systems [6]. The optical node arrays can be obtained using an on-chip system to integrate more nodes in the reservoir layer. For instance, a passive integrated photonics reservoir computing platform based on multimodal Y-junctions was proposed in [7]. In their designed structure, the system allows for upscaling the number of nodes as loss build-up can be limited. Another family of reservoirs with photonic nodes is based on free-space optics principles. An optical scheme performing reservoir computing over very large networks potentially being able to host several millions of fully connected photonic nodes was proposed [8]. The experiment result shows that this structure has a better performance with less computation time. However, most existing reservoir computing units, such as delay-based reservoir computing, spatial reservoir computing, have a significant influence on performance by the number of nodes in the reservoir layer. When scaling up the number of nodes in the reservoir layer, the computational cost is overhead dramatically [9].

We have recently reported simulation results on a novel all-optical RC based on photonic time-stretch and spectral mixing [10], In this paper, we experimentally demonstrated an idea. According to the characteristic of time stretch, there is a mapping between wavelength and time for a stretched ultrashort pulse. We have selected wavelength as nodes in the reservoir layer. In this way, the scale of the nodes is increasing significantly. The spectral mixing can realize the interaction between different neurons. Compare with the previous RC structure, this has simplified the RC structure and improved the performance.

II. Principal

The schematic of the proposed all-optical Reservoir Computer is shown in Fig. 1. An ultrashort pulse is emitted from the mode-locked laser (MLL) and was time-stretched by a dispersion compensating fibre (DCF). After being amplified by an Erbium-doped fibre amplifier (EDFA), the time-stretched optical signal was sent into a Mach-Zehnder Modulator (MZM). In a typical RC, there are three layers: input layer, reservoir layer, and readout layer. In the input layer, the signal to be classified was masked in an Arbitrary Waveform Generator (AWG) and modulated to the optical link. The random mask matrix defines the coupling weights

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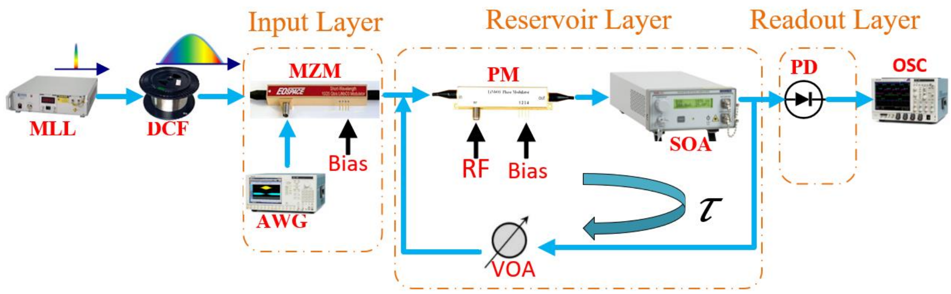

Fig. 1: The schematic of the proposed all-optical reservoir computer. MLL: Mode-Locked Laser, DCF: Dispersion Compensating Fibre, MZM: Mach-Zehnder modulator, AWG: Arbitrary Waveform Generator, PM: Phase Modulator, VOA: Variable Optical Attenuator, SOA: Semiconductor Optical Amplifier, PD: Photodetector, OSC: Oscilloscope.

from the input layer to the reservoir layer. The obtained input masking sequence is repeated for every time interval.

In the reservoir layer, a ring topology structure is adopted to update reservoir states in this work. The updated states of the reservoir can then be defined recursively as:

$$X_{n+1} = f_{NL}(WX_n + W_{in}u_n) \quad (1)$$

where u_n is the vector of the input data in the input layer. W is a random, square matrix, achieving reservoir connections in the reservoir layer. W_{in} is the input weights, which is a fixed, random matrix. x_n is the states in the reservoir. f_{NL} is a nonlinear activation function. In the proposed RC structure, the spectral mixing process is achieved in a phase modulator (PM) driven by a sinusoidally signal. The non-linear process is achieved by a semiconductor optical amplifier (SOA).

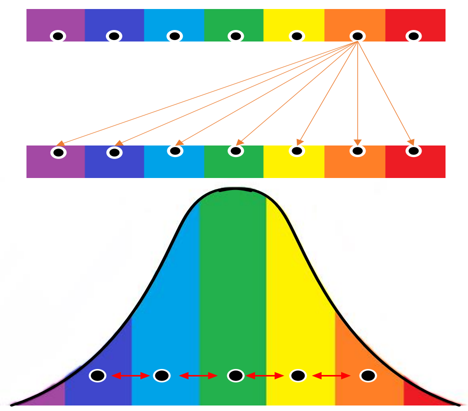

Fig. 2: The proposed nonlinear spectral mixing in photonics time stretch using phase modulation and optical semiconductor amplification.

According to the pulse temporal stretch, the time-stretched gaussian pulse has a corresponding relation between the wavelength and time. Hence, the wavelength is selected as the node in the reservoir layer. The phase modulator can achieve spectral mixing between wavelength neurons. As shown in Fig. 2, under a gaussian envelop, there has the spectral mixing between different wavelengths. This enables a richer dynamics statue in the reservoir layer, which is determined by the driven signal of PM and SOA.

Then, the signal was sent to a photodetector (PD) to collect reservoir status, the other is used as feedback corresponding to the memory function in RC. The feedback strength ratio is controlled by a variable optical attenuator. The output layer can be described as:

$$y_n = W_{out} f_{NL,out}(X_n) \quad (2)$$

where $f_{NL,out}$ is an optional output nonlinear activation function. W_{out} is a matrix containing the output weights trained by some optimization routine.

III. Experiment Results

In this section, a proof-of-concept experiment has been designed and implemented based on conceptual schematic shown in Fig. 1. To verify the proposed RC scheme, the basic waveform task (interleaved square and triangle waves classification) is performed. The corresponding expected output label is set to -1 and 1. The target waveform and output label is shown in Fig. 3.

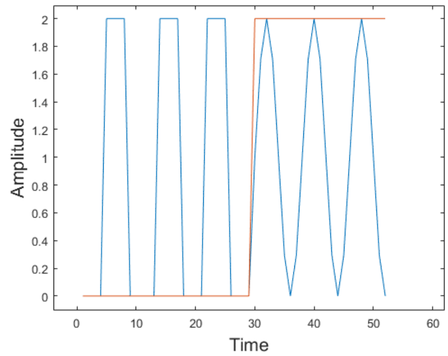

Fig. 3: The input data and corresponding output label.

A mode-locked laser (Calmar Mendocino FP laser) is used as the optical source to generate a series of ultrashort (800 fs) broadband (12 nm) pulses with a repetition rate of 50 MHz. The pulses are time-stretched with total dispersion of -1.04 ns/nm provided by a dispersion compensating fibre from 800 fs to ~12 ns. In the input layer, 400 random values chosen from a binary set (0, 1) are used as the input mask. A 20 GHz sinusoidal signal is used to drive the phase modulator. The driven current of SOA is set to 500 mA. In the readout layer, 400 updated statuses are collected for each stretched optical pulse as shown in Fig. 4. The linear regression approach is used to calculate the output.

In general, the performance of RC is indicated by the Normalized Mean Square Error (NMSE) between the reservoir output and the expected values for the test data. The NMSE can be described as:

$$NMSE = \frac{\langle (\bar{y}(n) - y(n))^2 \rangle_n}{\langle (\bar{y}(n) - \bar{y}(n))^2 \rangle_n} \quad (3)$$

where $y(n)$ is the reservoir output, and $\bar{y}(n)$ is the target output. $< >_n$ denotes the average over the discrete time steps. The NMSE is always a positive value, with lower NMSE values corresponding to better performances. In the training phase, 24 waveforms are used. In the testing phase, 4 waveforms are used. The classification result is shown in Fig. 5.

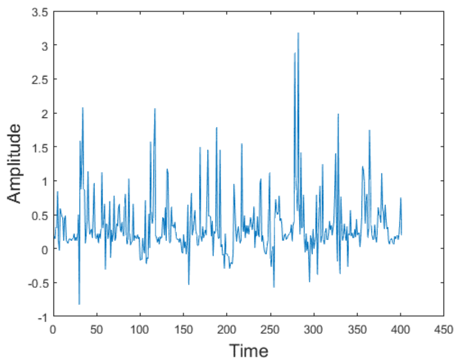

Fig. 4: Reservoir output weight.

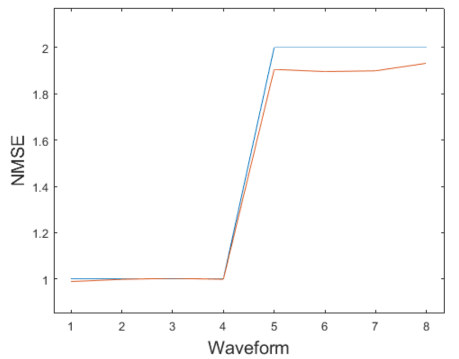

Fig. 5: Experiment results for a waveform classification task.

Fig. 5 shows the result of waveform classification for the task. The blue curve represents the target output level. The red curve represents the classified output level. As can be observed in the figure, different waveforms can be classified correctly (Output Label 1 represents square waves, and Output Label 2 represents triangle waves). The NMSE for this task is 0.14. The accuracy can be still improved by increasing the number of nodes.

In Fig. 6, we depict the NMSE as a function of the number of virtual nodes. The optimal value lies around N = 600. When N is larger, this would cause many more computational resources cost. When N is smaller, the classification performance is decreased. The minimal NMSE is as low as NMSE = 0.098.

IV. Conclusion

In this paper, we have experimentally demonstrated an all-optical reservoir computing method based on photonic time

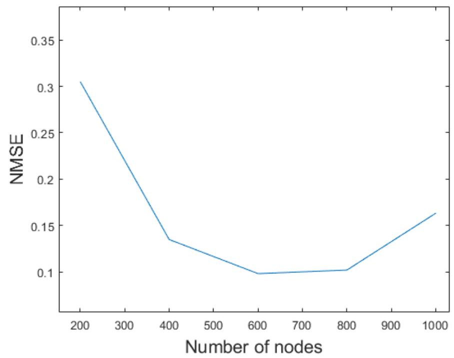

Fig. 6: Performance of waveform classification task as a function of number of nodes.

stretch and nonlinear spectral mixing. This method adapts photonics reservoir computing with spectral mixing to generate wavelength nodes in the reservoir layer. As a proof-of-concept experiment, the proposed all-optical RC with wavelength node has a better performance in waveform classification task. We have also demonstrated the relation between the nodes and NMSE.

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