Nanophotonic Reservoir Computing for Noisy Time Series Classification

M. R. Salehi, E. Abiri, and L. Dehyadegari

Abstract—Reservoir computing is known as a recent training concept in machine learning. This method is particularly useful in solving a broad category of categorization and recognition problems. The aim of this paper is using photonic reservoir computing for noisy time series classification. A complex network of photonic crystal cavities is used for modeling photonic reservoir computing. Applying nanophotonic reservoir computing resulted in perfect (100%) recognition accuracy for noise-less time series classification, and an accuracy of about 98% for noisy time series, which shows improvement (an amount of 3%) compared to previous works.

Index Terms—Nanophotonic reservoir computing, time series classification, photonic crystal cavities.

I. INTRODUCTION

Reservoir computing is a newly proposed method [1]-[3] in the field of machine learning which is a recurrent neural network with sparse and random weights. As an instant, these networks are used in classification problems such as dynamic pattern recognition [3], chaotic time series classification and recognition [4], speech recognition [5]-[7] and noise modeling [4].

Photonic reservoir computing is a platform for reservoir computing using photonics technology. A network of interconnected optical structures can outperform electronics in speed, bandwidth and power use [8]. A nanophotonic reservoir with coupled nonlinear photonic crystal cavities reveals a rich dynamical behavior and can be made use of to perform optical signal processing.

Due to unique nonlinear effects, small size, high speed and very low energy consumption, photonic crystal cavities are good candidates for all cases of optical reservoir computing. High Q-factor photonic crystal cavities enable greater interaction with the matter and result in more interesting dynamics. They can start to self-pulsate due to generation of free carriers and changing of the refract index [9], [10]. Thereby we will demonstrate how these properties emulate the behavior of spiking neurons on a photonic chip [11].

This paper aims to model reservoir computing scheme using photonic crystal cavities and also intends to study the function of this structure on noisy time series recognition. Section II below describes photonic reservoir computing in detail and demonstrates coupled mode theory (CMT) equations for modeling photonic crystal cavities as reservoir nodes. Time series categorization and obtained results will be discussed in Section III, and finally Section IV summarizes the main findings of this paper.

II. PHOTONIC RESERVOIR COMPUTING

Photonic reservoir computing is a photonic circuit which is a hardware implementation of reservoir networks. Nonlinear optical components provide a very energy-efficient and rich dynamic for classification and recognition problems.

A. Principles of Reservoir Computing

Neural networks are an example of human computational power, and reservoir computing is a type of recurrent neural networks which avoids the problems of training weights [8]. In reservoir computing framework, a randomly fixed recurrent neural network that is left untrained is excited with an external stimulus. A nonlinear mapping of the input signal into a high dimensional feature space is essentially performed by the reservoir. The readout function maps the resulted feature space to the desired output by a simple linear regression function [12].

Fig. 1 shows the reservoir which consists of reservoir, readout and its input and output.

Eq. 1 shows the reservoir dynamics:

\[ x(t+\Delta t)=(1-\eta)x(t)+\eta f_{in}(u(t)+w_{res}x(t)) \]  

(1)

where \( p_{out} \) and \( \varphi_{out} \) are output power and phase of the reservoir, \( p_{in} \) and \( \varphi_{in} \) are input power and phase, \( h(r) \) shows the gain \( g \) integrated over the length \( L \) of the amplifier, \( r \) and \( E_{out} \) show carrier lifetime and gain saturation, \( \beta \) is line width enhancement factor and \( g_{0} \) indicates small signal gain [13].
Since the training of weights is limited to the readout function, it is much simpler than that of other neural networks to have a hardware implementation of this structure. Nanophotonics provides us with some candidates for this purpose such as optical amplifiers [5], [14], lasers and photonic crystal cavities. Nonlinear characteristics, dynamic behavior, very energy efficient and high speed lend photonic crystal cavities a complex behavior for implementation of reservoir computing.

B. Photonic Crystal Cavities Simulation Model

CMT equations have been used for modeling photonic crystal cavities [10], [11]. This model captures basic features such as the characteristic power of a cavity, carrier density, temperature, resonance frequency of the cavity, phase difference between two cavities and detuning from the resonant frequency.

The CMT equations are then [15]:

\[
\frac{d\alpha}{dt} = \left[ j\omega + \delta_a n_l - \omega \right] \frac{\gamma_{loss}}{2} a + k a_{in} \\
\frac{d\Delta T}{dt} = \frac{\Delta T}{\tau_{th}} + \frac{\Gamma_{th} \alpha \alpha}{\Gamma_{pf} \alpha} \frac{\Delta T}{\tau_{pf} \alpha} \\
\frac{dN}{dt} = \frac{N}{\tau_{cf}} + \frac{\Gamma_{FCA} \beta \alpha \alpha}{2\hbar\omega^2} \frac{\alpha a^4}{\Gamma_{FCA}} \\
\alpha_{out} = e^{j\phi} \alpha_{in} + ka
\]

where \( \alpha = |\alpha|e^{j\phi} \), with \( |\alpha| \) the energy in the cavity and \( \phi \) the phase. \( \alpha_{in} \) and \( \alpha_{out} \) are the amplitudes of the input and output lights. \( \Delta T \) is temperature difference with the surroundings, \( N \) shows the amount of free carriers, \( k \) is the coupling from waveguide to ring, \( \phi \) indicates phase propagation in the bus waveguide, \( \omega \) and \( \omega_0 \) are the resonance frequency of the cavity and the frequency of the input light respectively, \( \tau_{cf} \) and \( \tau_{in} \) are relaxation times for free carriers and temperature, \( \beta_n \) is a constant governing two photon absorptions, \( n_g \) is the group index, \( \rho_n \) indicates the density of the silicon, \( \gamma_{abs} \) shows the thermal capacity, effective volumes \( V_n \) and \( V_c \) corresponding with a physical effect \( \alpha \) and \( \gamma_{con}, \gamma_{out} \) are absorption and total losses in the cavity.

Numerical methods such as Runge-Kutta4 can be used to solve the CMT equations. To obtain the steady state curves, we keep the input wavelength as fixed and put the derivative of Eq. 2 equal to zero, and then simply parameterize \( \Delta T, N \) and \( P_{in} \) as a function of \( |\alpha|^2 \). Table I shows the parameter values.

As shown in the results (Fig. 2 and Fig. 3), the difference between slow heating effects and the fast free carrier dynamics causes self-pulsation (Fig. 2) and excitability (Fig. 3) in photonic crystal cavities. This nonlinear behavior suggests a network of photonic crystal cavities as a nanophotonic reservoir to perform optical signal processing.

![Image](https://via.placeholder.com/150)

**Fig. 2.** Results of simulations with CMT equations; in input wavelength \( \lambda = 1550\text{nm} \) and input power \( P_{in} = 0.6\text{mW} \) the photonic crystal cavity self-pulsates.

![Image](https://via.placeholder.com/150)

**Fig. 3.** Results of simulations with CMT equations; in input wavelength \( \lambda = 1550\text{nm} \) and input power \( P_{in} = 0.7\text{mW} \) the photonic crystal cavity is excitable.

**TABLE I: Parameter Values that Used in Simulations**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_n )</td>
<td>( 8.4\times10^{12} )</td>
<td>m.W^{-1}</td>
</tr>
<tr>
<td>( \sigma_n )</td>
<td>( 10^{-21} )</td>
<td>m²</td>
</tr>
<tr>
<td>( \rho_n )</td>
<td>( 2.33 )</td>
<td>g.m³</td>
</tr>
<tr>
<td>( c_p,n )</td>
<td>( 0.7 )</td>
<td>J.g⁻¹.K⁻¹</td>
</tr>
<tr>
<td>( n_m = n_g )</td>
<td>( 3.476 )</td>
<td></td>
</tr>
<tr>
<td>( \lambda_n )</td>
<td>( 1552.77 )</td>
<td>nm</td>
</tr>
<tr>
<td>( \tau_{ck} )</td>
<td>( 65 )</td>
<td>ns</td>
</tr>
<tr>
<td>( \tau_{cf} )</td>
<td>( 5.3 )</td>
<td>ns</td>
</tr>
<tr>
<td>( \Gamma_{th} )</td>
<td>( 0.9355 )</td>
<td></td>
</tr>
<tr>
<td>( \Gamma_{TPA} )</td>
<td>( 0.9964 )</td>
<td></td>
</tr>
<tr>
<td>( \Gamma_{FCA} )</td>
<td>( 0.9996 )</td>
<td></td>
</tr>
<tr>
<td>( V_{th} )</td>
<td>( 3.19 )</td>
<td>( \mu\text{m}^3 )</td>
</tr>
<tr>
<td>( V_{TPA} )</td>
<td>( 2.59 )</td>
<td>( \mu\text{m}^3 )</td>
</tr>
</tbody>
</table>
III. TIME SERIES CLASSIFICATION

A simple but non-partial noisy signal classification task was used in the simulation as in previous works [16], [17]. The time series have random switches between square and triangular wave forms. These two different time series were required to be classified and the output signal followed the inputs changes as fast as possible.

For better comparison, a reservoir with 25 nodes and waterfall topology [8] was drown on in experiments as used in earlier works [16], [17].

Fig. 4a shows an example of time series with its desired output while Fig 4b demonstrates reservoir state vectors (output power of photonic crystal cavities) for this time series, and Fig. 4c shows the output results of the readout and the final output by applying the sign function.

The fraction of time in which the reservoir gives a correct classification is defined as recognition accuracy. Photonic reservoir computing with a network of photonic crystal cavities resulted in 100% recognition accuracy for noise-less time series.

IV. NOISY TIME SERIES CLASSIFICATION

Noisy time series with different signal-to-noise ratios were used in this stage for classification. Fig. 5a shows an example of noisy time series with 20 db of signal-to-noise ratio and its desired output. Fig 5b shows reservoir state vectors and Fig. 5c demonstrates output results from the readout function. A White noise with different signal-to-noise ratios was used and the recognition accuracy was compared with previous works, as observed in Fig. 6.

Small size, high speed and very low energy consumption caused photonic crystal cavities good candidates for modelling optical reservoir computing. High Q-factor photonic crystal cavities are self-pulsate and were investigated for hardware implementation of reservoir computing.

V. CONCLUSION

In this paper a nanophotonic reservoir was drown on to perform optical signal processing. Unique nonlinear effects, The application of photonic crystal cavities as reservoir nodes resulted in perfect recognition accuracy for the time series without noise. For noisy time series with 20 to 60 db of signal-to-noise ratios the recognition accuracy varied between 99.82% to 100% which shows about 7% improvement over the previous work. These advantages suggested photonic reservoir computing with a network of photonic crystal cavities as a good candidate for other classification tasks and large signal processing, such as speech recognition.

REFERENCES

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