Advances in Photonic Reservoir Computing on an Integrated Platform

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ABSTRACT

Reservoir computing is a recent approach from the fields of machine learning and artificial neural networks to solve a broad class of complex classification and recognition problems such as speech and image recognition. As is typical for methods from these fields, it involves systems that were trained based on examples, instead of using an algorithmic approach. It originated as a new training technique for recurrent neural networks where the network is split in a reservoir that does the 'computation' and a simple readout function. This technique has been among the state-of-the-art. So far implementations have been mainly software based, but a hardware implementation offers the promise of being low-power and fast. We previously demonstrated with simulations that a network of coupled semiconductor optical amplifiers could also be used for this purpose on a simple classification task. This paper discusses two new developments. First of all, we identified the delay in between the nodes as the most important design parameter using an amplifier reservoir on an isolated digit recognition task and show that when optimized and combined with coherence it even yields better results than classical hyperbolic tangent reservoirs. Second we will discuss the recent advances in photonic reservoir computing with the use of resonator structures such as photonic crystal cavities and ring resonators. Using a network of resonators, feedback of the output to the network, and an appropriate learning rule, periodic signals can be generated in the optical domain. With the right parameters, these resonant structures can also exhibit spiking behaviour.

Keywords: photonic reservoir computing, integrated optics, semiconductor optical amplifiers, nonlinear optics, optical neural networks, speech recognition.

1. INTRODUCTION

Reservoir Computing (RC) is a training concept for Recurrent Neural Networks (RNNs), introduced a few years ago [1,2]. It comes from the field of machine learning where systems are trained based on examples. In RC a randomly initialized RNN, called the reservoir, is used but left untrained. The states of all the nodes of this reservoir are fed into a linear readout, which can be trained with simple and well established methods, usually linear regression. Hence, difficulties, such as slow convergence, associated with training a full recurrent network are avoided. For several complex machine learning tasks it has been demonstrated that RC equals or outperforms other state-of-the-art techniques. An example is the prediction of the Mackey-Glass chaotic time series several of orders of magnitude better than classic methods [1].

Most reported results on reservoir computing use a (randomized) network of hyperbolic tangent or spiking neurons. However, recent work has indicated that a wide range of sufficiently high-dimensional nonlinear dynamic systems can be used as a reservoir [3]. Most implementations thus far have been software based, hence the pursuit of finding a suitable hardware platform for performing the reservoir calculation. This transition offers the potential for huge power consumption savings and speed enhancement. Photonics is an interesting candidate technology for building reservoirs, because it offers a range of different nonlinear interactions working on different timescales.

In a previous paper we have shown that a network of Semiconductor Optical Amplifiers (SOAs) can be used as a reservoir on a benchmark speech recognition task [4]. In this paper we investigate some of the important design parameters of a photonic reservoir on the same task but with babble noise added to make it more difficult. Section 2 describes the design of classical reservoirs and section 3 the details of our photonic SOA reservoir. The isolated digit recognition task we use to compare classical and SOA reservoirs is discussed in section 4 and the obtained results in section 5. It turns out that the interconnection delay is a very important design parameter and that there is an optimal delay for this task. At this optimal delay coherent SOA reservoirs perform better then classical reservoirs.

2. RESERVOIR COMPUTING

Echo State Networks (ESNs) are an implementation of RC where all the nodes are hyperbolic tangent functions and the nodes are usually randomly connected [1]. The reservoir state **x**[t] is updated through the following formula:

$$\mathbf{x}[t+\Delta t] = \tanh(\mathbf{W}_{in}\mathbf{u}[t] + \mathbf{W}_{res}\mathbf{x}[t]), \quad (1)$$

where **u**[t] represents the inputs, the matrix $\mathbf{W}_{in}$ the weights for all connections from input to reservoir and $\mathbf{W}_{res}$ is the interconnection weight matrix of the reservoir. Although the reservoir itself remains untrained ($\mathbf{W}_{res}$ is kept fixed during training), its performance depends critically on its dynamical regime, determined by the gain and loss in the network. Optimal performance is usually obtained near the edge of stability, i.e. the region in between stable and unstable or chaotic behaviour, because the system's memory is optimized there. Hence, to obtain good performance, we need to be able to tune a reservoir's dynamic regime to this edge-of-stability. A common measure for the dynamic regime is the *spectral radius*, the largest eigenvalue of the system's Jacobian, calculated at its maximal gain state (for classical hyperbolic tangent reservoirs, this corresponds to the largest eigenvalue of the network's interconnection weight matrix $\mathbf{W}_{res}$). The spectral radius is an indication of the stability of the network. If its value is larger than one, the network might become unstable. Tuning the spectral radius close to one often yields reservoirs with close to optimal performance.

3. PHOTONIC RESERVOIR COMPUTING

Dedicated photonic hardware offers a lot of promise, but there are some fundamental differences between photonic and classical reservoirs. For example, optical information is usually encoded in changing power levels which are non-negative, in contrast to traditional RC which uses real values, and this makes it difficult to have negative weights and to subtract signals. In this paper we use coherent light which can be described by complex amplitudes $A = \sqrt{P}\exp(i\Phi)$ with P the power of the light and Φ the phase.

3.1 Semiconductor optical amplifiers

SOAs show gain saturation in their behaviour and that makes them the optical device closest to the hyperbolic tangent functions used in classical ESN reservoirs. That is the reason, besides being broadband and able to compensate losses in the network; we chose them as a first medium to verify the usefulness of photonic reservoirs. The resemblance can be seen in Fig. 1a showing the simulated steady state curve of an SOA and a scaled hyperbolic tangent. The similarity shows especially in the low-power regime (inputs < 1 mW) where the behaviour is near linear. This is the regime used for the simulations in this paper. The SOA model we use was proposed by Agrawal [5]. It captures the most important features such as gain saturation, carrier lifetime and gain dependent phase shift.

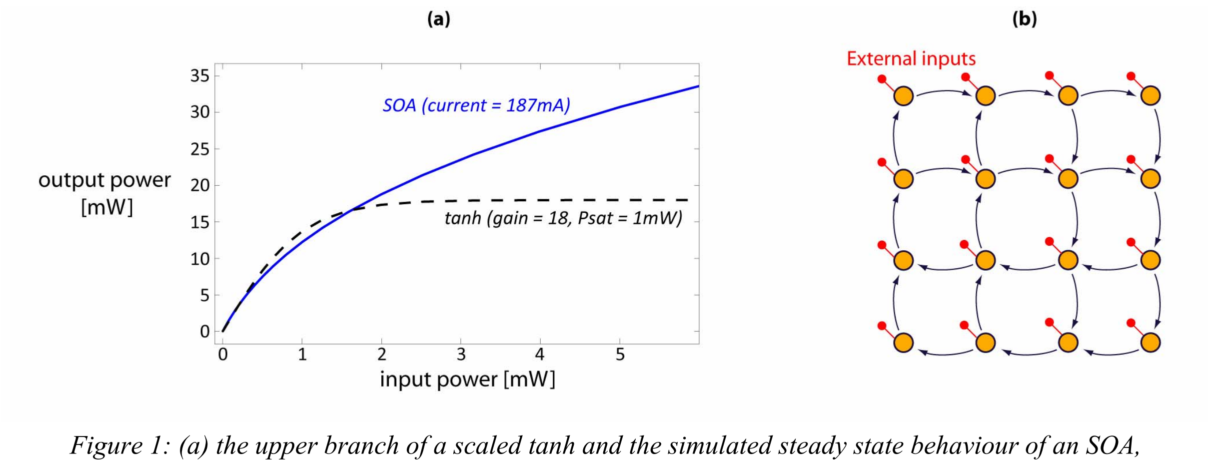

Figure 1: (a) the upper branch of a scaled tanh and the simulated steady state behaviour of an SOA, (b) 4x4 swirl topology,

3.2 Topology

The topology used throughout the simulations is called a *swirl* topology as the information rotates through the network (Fig. 1b). It can be easily enlarged, while keeping the length of all connections equal. It is a nearest-neighbour topology which is easier to make on a planar chip, than random networks. We lose some freedom in connectivity that exists in software implementations, but avoid the need for a lot of crossings. Since RC was initially conceived for RNNs, it is important to have some feedback connections in the network, hence the swirling of the network. Having the same length for every connection makes it easier to investigate and model the influence of certain connection parameters. Every connection is defined by three parameters: the time delay

Δt it introduces, the phase change $\Delta\Phi$ and the loss ΔP . The loss determines the total amount of gain and loss in the network and hence the value of the spectral radius. As was mentioned in the beginning of section 3 the light is represented by complex amplitudes and since the connections influence both the phase and loss of the light they act as complex weights. Therefore to incorporate the influence of coherence and interference the spectral radius has to be calculated from the now complex interconnection matrix $\mathbf{W}_{res}$, while also including the gain of the SOAs. Therefore the maximum gain of every SOA, i.e. at zero input (Fig. 1a), has to be incorporated in $\mathbf{W}_{res}$.

4. SPEECH RECOGNITION

Speech recognition is very difficult to solve but reservoir computing with classical neural networks has been employed with success [6]. The task used in this paper is the discrimination between spoken digits, the words 'zero' to 'nine', uttered by 5 female speakers. The dataset and the simulation framework for classical reservoirs is publicly available [7]. As is standard for speech recognition, some pre-processing of the raw speech signal is performed before it is fed into the reservoir. Often these methods involve a transformation to the frequency domain and highlighting certain frequencies specific for the ear by using some kind of ear model. The model used for the results in this paper was the Lyon ear model [8]. We added babble noise from the NOISEX database, with a signal-to-noise ratio of 3 dB to increase the complexity of the task [9]. The performance is measured with the Word Error Rate (WER), which gives the ratio of incorrectly classified samples to the total number of samples.

Reservoir memory is related to the typical time scales of the reservoir itself. Therefore, to achieve optimal memory in a reservoir, the relevant time scales of the input signals must be adapted to those of the physical reservoir implementation. Audio signals are very slow, so we accelerated the speech signal to accord with timescales typical for the delays in our SOA network. The new durations of the digits are in the order of a few hundred ps. Hence, although we use this task to demonstrate the potential of photonic reservoir computing, we do not propose to use photonic reservoirs as a platform for standard real-time, slow audio signals.

5. RESULTS

In our experiments the input consists of 77 channels, coming from the pre-processing of the speech data. With such high-dimensional input, the number of nodes needs to be sufficiently large. All the experiments were therefore done with a rectangular 9×9 swirl network of 81 nodes. Before feeding input to the network, the different channels were mixed together in a random manner for every node and made non-negative by shifting them upwards with the minimum over all the inputs. The output of all the nodes is given to ten linear classifiers (one for every digit). These classifiers are trained on a part of the dataset and tested on a different part. The classifier with the strongest response for a certain input 'wins'.

For every simulation a sweep was done over the loss and phase change $(\Delta P, \Delta\Phi)$ in every connection. The loss affects the spectral radius. A result of such a sweep is shown in Fig. 2. The darker a region, the better the performance. In this case a very short delay time was used (6.25 ps) and the optimal performance is only obtained for a very narrow phase region. Phase is important, since it determines the interference of the light when it combines in front of every SOA. In fact, below the instability boundary (spectral radius < 1), the reservoir is much more sensitive to phase than it is to gain.

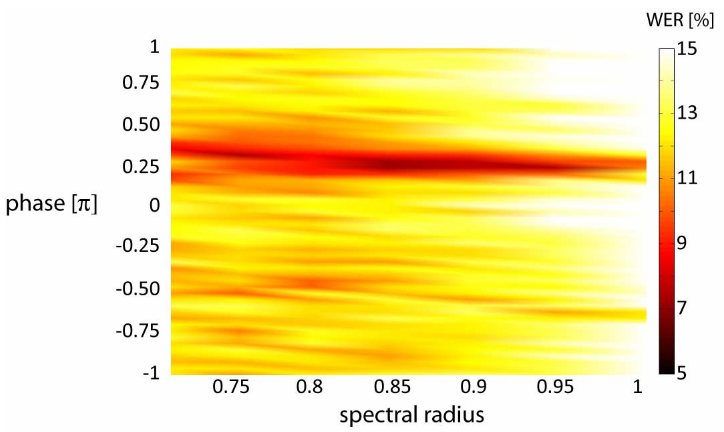

Figure 2. Performance of a coherent SOA network with swirl topology and a delay of 6.25 ps.

5.1 Delay

The third parameter that defines the connections is the time delay. If we change this parameter and take each time the optimal result of the kind of sweep described in the previous section, we get a plot as in Fig. 3. First of all this figure shows that there exists an optimal delay for a given duration of the audio signal and the optimal delay corresponds to roughly half of the length of the speech signal. Second, it shows that classical networks with real-valued information perform worse than coherent networks with a complex-valued representation of information, no matter if the node is an SOA or a tanh. This makes that coherence has an added value for reservoirs when the phase can be controlled and that the interconnection length is a very important design parameter for SOA reservoirs.

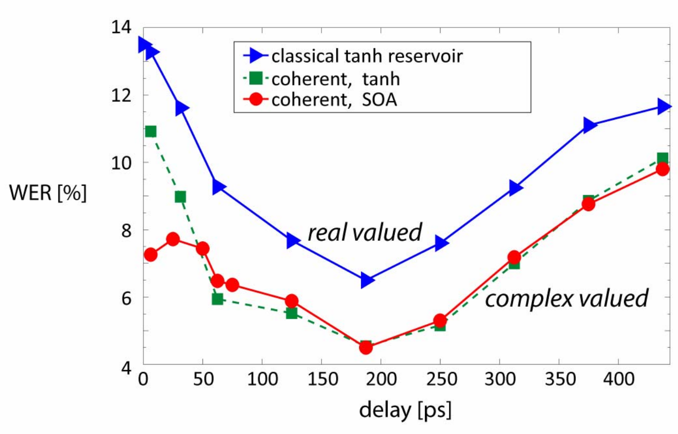

Figure 3. Performance of a classical tanh reservoir with real-valued information compared with two coherent networks. All networks have a swirl topology and an optimal performance at the same interconnection delay.

6. CONCLUSIONS

We have shown that a network of SOAs can be used as a reservoir for reservoir computing on an isolated digit recognition task and identified delay as an important design parameter. A network with optimal delay and coherence achieves even better results on this task than classical real-valued tanh reservoirs. Future research will focus on making a small-scale hardware implementation to validate the simulation results of this paper.

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