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Delays in photonic reservoir computing with Semiconductor Optical Amplifiers

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Reservoir Computing is a methodology coming from the field of machine learning and neural networks that has been successfully used in pattern classification problems. We have investigated with simulations a network of coupled semiconductor optical amplifiers as an integrated photonic reservoir on a benchmark speech recognition task. In spite of the differences with classical software reservoir models, the performance of our photonic reservoir is comparable to that of conventional implementations with the same number of nodes. It performs even better when the most important parameter, the amount of delay in the interconnections, is tuned to its optimal value.

Introduction

Reservoir Computing (RC) is a training concept for Recurrent Neural Networks (RNNs), introduced a few years ago [1,2] coming from the field of machine learning where systems are trained based on examples. In RC a randomly initialized RNN, called the *reservoir*, is used and left untrained. The states of all the nodes of the RNN are then fed into a linear readout, which can then be trained with simple and well established methods. Usually, a mere linear regression is used. Hence, the difficulties of training a recurrent network are avoided as only the readout is changed. Reservoir computing has been demonstrated to equal or outperform other state-of-the-art techniques for several complex machine learning tasks. An example is the prediction of the Mackey-Glass chaotic time series several of orders of magnitude better than classic methods [1].
Although the reservoir itself remains untrained, its performance depends drastically 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 behavior, because this regime optimizes the system's memory. 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). 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.

Photonic reservoir computing

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 suffi-

ciently high-dimensional nonlinear dynamic systems can be used as a reservoir. One way of explaining the success of reservoir computing is to view the reservoir as performing a high-dimensional spatio-temporal pre-processing or filtering of the input. In this view, the reservoir essentially mixes the inputs together, so that the interesting features are more easily extracted by the readout. A nonlinear mixing often seems to offer advantages over linear mixing when dealing with more complicated problems such as speech recognition. 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. It also offers the promise of being more power efficient. There remain, however, many challenges. If you encode the information in changing power levels, then it becomes difficult to have negative weights and to subtract signals. A topology made on a 2D chip, which is the case for most photonic chips nowadays, limits the freedom in connectivity that exists in software implementations, since one would like to minimise the number of crossings. When using a coherent light source, the amplitude and accompanying phase start to play a role as well, whereas traditional RC is only amplitude based.
In a previous paper we have already shown that a network of Semiconductor Optical Amplifiers (SOA) can be used as a reservoir on a simple signal classification task [3].

Speech recogntion

Speech recognition is a very difficult problem to solve but reservoir computing with classical neural networks has been employed with success for speech recognition [4]. 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 [1]. 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 typical for our ear by using some kind of ear model. The model used for the results in this paper was the Lyon ear model [5]. We added babble noise from the NOISEX database, with a Singal-to-Noise Ratio (SNR) of 3 dB [2] to increase the complexity of the task. The performance is measured with the Word Error Rate (WER), which gives the ratio of incorrect classified samples and the total number of samples. The best results achieved with classical reservoirs was around 7 %.
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 rather slow, so we accelerated the speech signal to accord with timescales typical for the delays in a network of SOAs (duration of one digit 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.

[1] http://snn.elis.ugent.be/rctoolbox
[2] http://spib.rice.edu/spib/select_noise.html

SOA model

SOAs, with a saturation of gain and output power, are the optical device closest to the hyperbolic tangent functions used in many ANN implementations. That is the reason we chose them as a first medium to verify the usefulness of photonic reservoirs. The SOA model we used is one proposed by Agrawal [6]. It captures the most important features such as gain saturation, carrier lifetime and phase shift depending on the gain.

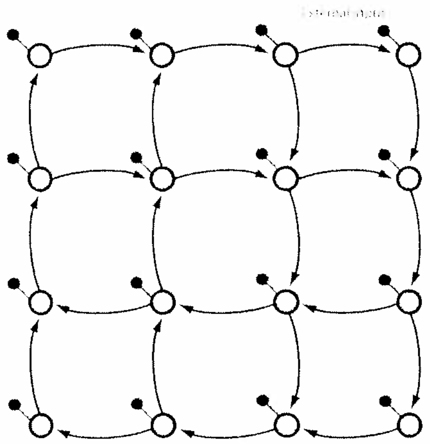

Figure 1: The swirl topology used in our simulations

Results

In our experiments the input consists of 77 channels, resulting 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 done with a network of 81 nodes. An example of the topology used can be seen in Fig. 1, showing a network of 4 by 4 SOAs. We call this a *swirl* topology. All the connections are nearest neighbor connections and this topology can be easily enlarged, while keeping the length of all connections equal.
In the experiments we swept two variables: the phase change and attenuation in every connection. The attenuation affects the spectral radius. Because we work with complex amplitudes and to incorporate the influence of coherence, the spectral radius has to be calculated from the complex interconnection matrix, also including the gain in the SOAs. When we change a design parameter, e.g. the delay in the interconnections, such a sweep is done for all the values of that parameter. When we take the best value for every sweep, we can summarize the results as in Fig. 2. It shows that there exists an optimal delay in the network resulting in an optimal performance of around 5 %, better than the best results of classical networks.

Delays in photonic reservoir computing with SOAs

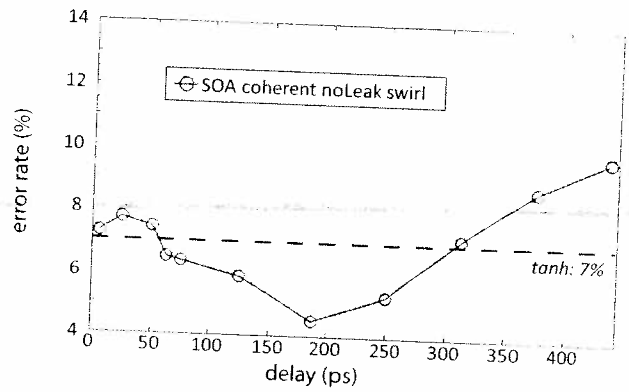

Figure 2: Result of a network of SOAs with different delay in between them on a isolated digit recognition task

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 SOAs achieves even better results on this task than classical methods.

Acknowledgments

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