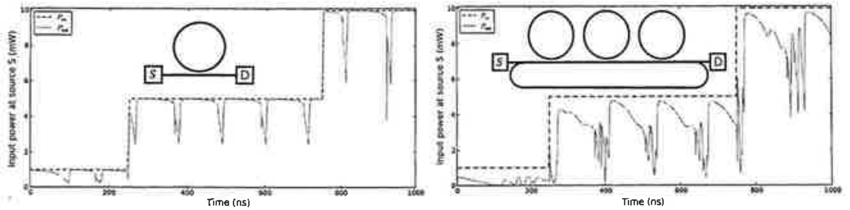

(a) Self-pulsation in a single (all-pass) microring (b) Dynamics of a system with three (all-pass) microrings coupled with a feedback loop

Figure 3: Time-domain simulations

Given the different timescales and the compact formulation of the basic equations, our tool is very well suited to simulate this system. In Fig. 3(a) we show how different fixed input powers can trigger the experimentally observed self-pulsation in an all-pass filter. In Fig. 3(b) we investigate a system of three coupled self-pulsating microrings with an external feedback loop.

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Delays in photonic reservoir computing with semiconductor optical amplifiers

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Reservoir computing is a decade old framework from the field of machine learning to use and train recurrent neural networks and it splits the network in a reservoir that does the 'computation' and a simple readout function. This technique has been among the state-of-the-art for many classification problems. So far implementations have been mainly software based, but a hardware implementation offers the promise of being low-power and fast. We will show that photonic reservoirs can achieve an excellent performance on a benchmark isolated digit recognition task, if the interconnection delay is optimized and the phase controlled. Furthermore we will show that this optimal delay is dependent on the input speed of the audio signal.

Introduction

Reservoir Computing (RC) is a training concept for Recurrent Neural Networks (RNNs), introduced a decade 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. 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 unity, the network might become unstable. Tuning the spectral radius close to unity 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 and most 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.

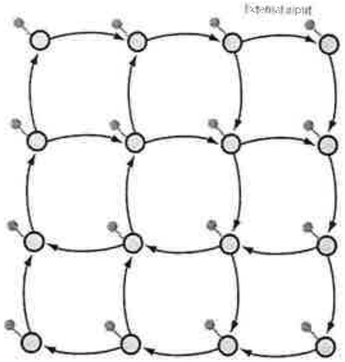

Figure 1: The swirl topology used in our simulations

Photonics is an interesting candidate technology for building reservoirs, because it offers a range of different nonlinear interactions working on different timescales. Semiconductor Optical Amplfiers (SOAs), with a saturation of gain and output power, are the optical device closest to the hyperbolic tangent functions used in many RC 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 [3]. It captures the most important features such as gain saturation, carrier lifetime and phase shift depending on the gain.

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 [5]. 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 are 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. We used the Lyon ear model which highlights certain frequencies typical for our ear [6]. We added babble noise from the NOISEX database, with a Signal-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 is the ratio of incorrect classified samples and the total number of samples.

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[1] `http://snn.elis.ugent.be/rctoolbox`

[2] `http://spib.rice.edu/spib/select_noise.html`

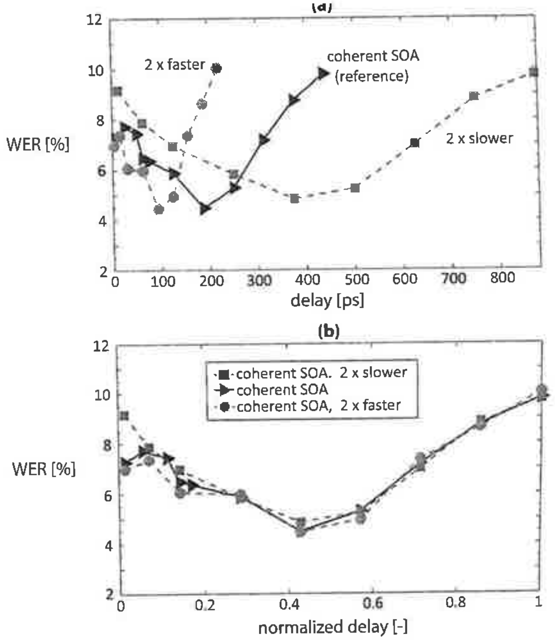

Figure 2: (a) Results for different speeds of the input signals fed into a coherent swirl SOA reservoir, (b) the same results but plotted on top of each other by changing the X-axis of the different curves the same way as their input rate.

Results

In our experiments the input consists of 77 channels, coming out of the Lyon model. With such high-dimensional input, the number of nodes needs to be sufficiently large. Therefore all the experiments were done with a network of 81 (9×9) nodes in a *swirl* topology (Figure 1). 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 Figure 2. It shows that there exists an optimal delay in the network.

In a previous paper we have shown that despite several differences between photonic and classical reservoirs (e.g., topology constraints, complex-valued signals and interconnection delays), the use of coherent light in a well-tuned SOA reservoir architecture offers significant performance benefits [4]. The most important design parameters are the delay and the phase shift in the system's physical connections and with optimized values for these parameters, coherent SOA reservoirs can achieve better results than traditional simulated reservoirs.

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).

It is however interesting to know whether our delay results depend completely on the speech signal itself. In that case we expect the optimal delay to shift according to the input rate. This is actually what happens as can be seen in Figure 2 where the optimal results in function of the interconnection delay are shown for rates two times slower and two times faster than our previous experiments. The (a) part shows that, as the speed increases or decreases, the optimal delay shifts as well. In (b) we have rescaled the X-axis for the different curves the same way as their input rate, so their X-axes all match that of the original one (solid curve–triangles). Here the similarity between the three graphs implies that the optimal delay is indeed a feature of the audio signals themselves as it shifts according to the input rate. This also means that, confronted with a hardware implementation of a photonic reservoir with certain delays, we can change the input rate to match the delays. For slower signals there is no reason why this should break down, although there are practical limitations to delay lengths on a chip since losses increase with length and they consume area. For ever faster signals at some point the delay in the SOAs will dominate the interconnection delays.

Conclusions

We have shown with an isolated digit recognition task that a network of SOAs can be used as a reservoir for reservoir computing and we identified delay as an important design parameter and showed that its value depends on the input speed of the speech signal.

Acknowledgments

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Test of InP-based Mach Zehnder modulator for radiation hardness

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High Energy Physics experiments at CERN in the Large Hadron Collider for example, employ a plethora of mixed-signal integrated circuits to detect particles. Digital read-out architectures of such particle detector circuits are complex and demand high speed serial links. Detector circuits demand data rates of multiple Gbps per chip and several Tbps for the whole detector and this demand is ever increasing as experiments progress to higher luminosities. Possible solution to tackle the problem of high data rates is to transport data optically by external modulation of a continuous wave laser.

The detector circuits have to operate in a high radiation environment and particles passing through the circuits alter the properties of the circuits giving rise to performance issues.

In this work, we investigate the radiation hardness performance of InP-based Mach-Zehnder modulators. The modulator circuit is mounted on a small PCB and irradiated with a 24 GeV/c proton beam at CERN up to various fluencies. The irradiated samples are then characterized and compared against measurements of non-irradiated devices.

Introduction

High Energy Particle Physics (HEP) experiments at CERN in the Large Hadron Collider for example, collide particles (protons or heavy ions) against each other and employ a wide range of detectors to detect particles that originate out of the interaction. These detectors are comprised of various sensor elements and electronic circuits to read out the sensors. Digital read-out architectures of such particle detector circuits are complex and demand high speed serial links to send enormous amounts of data to a computer farm. This demand for bandwidth is ever increasing as experiments progress to higher luminosities. Detector circuits demand serial data rates in multiple Gbps per chip and several Tbps for the whole detector. Copper co-axial cables combined with CMOS technologies are seen reaching their limits at data rates of 10 Gbps for a couple of meters of cable. Possible solution to tackle the problem of high data rates is to transport data optically.

The detector circuits have to operate in a high radiation environment [1]. Particles passing through the circuits causes trapping of charges at interfaces, cause damage to crystal structure etc giving rise to performance issues. State of the art techniques include reading out the data on electrical links for the first couple of meters. At this stage, the data is transmitted optically by directly modulating a Laser diode on to a fiber. The photo-detectors are placed in the computer farm about hundred meters away to read the optical data. The radiation levels are orders of magnitude lower already at a distance of couple of meters. With data rates going high, even these relatively short distance electrical connections are becoming a significant challenge. Performance of Lasers degrade significantly already at less severe radiation environments [2]. Hence, Lasers

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