A Novel Photonics Approach to Unconventional Information Processing

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Abstract We present a novel scheme in which photonic information processing can be performed using a photonic system with delayed feedback. Inspired by the way our brain process information, we show that a single optoelectronic oscillator with delay can replace a complex network of nonlinear dynamical elements without losing performance.

Introduction

Photonic-based information processing is a vision originating from the early 1980s¹, which has been receiving reawakened interest with the evolution of photonic technologies and quantum computing². A main issue in the success of photonic-based information processing is that special-purpose computationally efficient optical devices should be presented in terms of their energy costs and applicability to general-purpose computation³.

In this work, we highlight a novel scheme in which photonic information processing can be performed using an optical system with delayed feedback. Unlike traditional computers, where the processing of information is typically handled in a sequential manner, a novel computational paradigm known as reservoir computing⁴⁻⁶ has recently emerged.

Reservoir computing⁴⁻⁶ (RC) is a recently introduced computing paradigm inspired in the way our brain appears to process information. In conventional RC, a recurrent neural network (RNN) is used as a reservoir that is not trained but instead read out by a simple external classification layer, as shown in Figure 1 (top). This recurrent network can perform information processing by using the transient response occurring in a complex system due to an input signal. It has been shown that RC serves universal computational properties; any potential operation could be realized, outperforming other approaches for certain tasks^{5,7}. While numerical implementations of this concept exist, optical hardware implementations of such complex networks are still lacking.

In this context, we replace complex networks by simple delay systems without losing functionality. Delay-based architectures reduce the usually required large number of nodes to only few, or even one nonlinear element with delayed coupling, as shown in Figure 1 (bottom). The delay line is divided in equidistant virtual nodes that can be addressed via time

multiplexing⁸.

Using delay systems, similar or even better performances than conventional RC approaches are found in certain tasks. Recently, it was shown that a single nonlinear electronic oscillator with feedback, the simplest form of a delayed system, can indeed perform information processing with very good results in speech recognition and time series prediction tasks⁸.





Delay systems fulfill the required demands of high-dimensionality and fading memory, essentials for RC⁸. The suggested approach simplifies the RC concept, opening new ways for high-speed photonics implementations and first results are already appearing^{9,10}.

In contrast to digital electronic computing, our approach computes in an analog fashion by using light intensity to encode data. In analog optical computing, the finite signal-to-noise ratio (SNR) of the practical implementation is a major limiting factor. In particular, we have observed that the performance of certain computational tasks, e.g. time-series prediction, degrades significantly when the SNR is lowered. Here, we optimize the pre-processing techniques and the parameters of this analog optical system to minimize its sensitivity to noise.

Experimental implementation

Our hardware implementation of the RC concept is based on an optoelectronic oscillator with delay, which is depicted in Figure 2. The experimental implementation is composed by a semiconductor laser diode, an integrated optics Mach-Zehnder modulator (MZM) performing a sine squared non-linear transformation, a fiber delay line, and an optoelectronic feedback for intensity detection, filtering, and amplification. The feedback signal serves as the drive of the MZ modulator, closing the delayed oscillation loop (delay time 21μ s). This optoelectronic oscillator allows the dynamical regimes typically observed for the Ikeda dynamics, including a period doubling route to chaos.



Fig. 2: Experimental implementation of the optoelectronic oscillator with delay.

Figure 3 shows the power spectrum of the oscillator response once the system is driven into the chaotic regime¹¹. As it can be seen in Fig. 3, relevant spectral contributions can be estimated up to ~ 6 MHz. This hardware implementation of a photonic realization of reservoir computing with an optoelectronic oscillator allows for information processing at MHz speeds. However, all-optical photonic implementations and/or high-speed electronic components can eventually push the information processing speed towards the GHz range.



Fig. 3: Power spectrum of the delayed optoelectronic oscillator in the chaotic regime.

Experimental results

In order to evaluate the capability of the nonlinear optoelectronic oscillator to process information, we test the performance of the system to solve several benchmark tasks, e.g. spoken digits recognition and time-series prediction⁹. These tasks are computationally

hard with standard computing machines.

Previous results show that an optoelectronic oscillator with delayed feedback can indeed replace a complex network and perform information processing⁹. In particular, this dynamical system is capable of identifying isolated spoken digits with excellent performance. The reported performance is a single misclassification in 500 independent digits after the system is trained⁹ (0.2% word error rate), comparable to current state of the art.

For RC purposes, the system needs to be biased in a stable regime (fixed point of the dynamics) without external input. However, the addition of an external input induces a complex transient response in the dynamical system. The information processing task is realized by exploiting the transient response of the system.

For the information processing, each sample of the input signal is expanded over a time interval of length 21μ s (delay time) and multiplied by a pre-processing mask before is injected into the nonlinear oscillator⁸. Here, we employed a multi-valued pre-processing mask, in which the amplitude levels are randomly distributed over the delay interval, to overcome the finite SNR of the practical implementation.

This optoelectronic set-up is a versatile system. In particular, the performance of the system depends significantly on the operating point⁹, which can be tuned via the MZM bias. In Figure 4 (top) and (middle), we show the tuning of the nonlinearity and the operating point when the MZM voltage is varied.



Fig. 4: Experimentally recorded (top) nonlinearity and (middle) operating point as a function of the Mach-Zehnder bias voltage (phase offset). (bottom) Prediction error (NMSE) for the Santa Fe time-series prediction task.

As an example, we show in Figure 4 (bottom), the performance of the optoelectronic oscillator for a time-series prediction task, using

as input the experimental data of Lorenz-like laser chaos (Santa Fe test)¹², as a function of the operating point. The lowest prediction error (NMSE) is 0.02 (see inset for an improved scan with larger SNR around the best operating range), comparable to a standard reservoir with 50 nodes¹². Therefore, a good performance is obtained despite the finite SNR of the detection apparatus¹¹, which is estimated to be equivalent to a 10 bits resolution.

Modelling

The experimental hardware realization of the optoelectronic oscillator with delayed feedback can be described by the following dynamical equation¹³:

$$dx(t)/dt = -x(t) + \beta \sin^{2} [x(t - \tau) + \phi + \gamma u(t)], (1)$$

where t is the time in normalized units (t = t/(240 ns), β is the feedback strength, τ is the delay time, ϕ is the Mach-Zehnder phase, γ is the input scaling and u(t) is the external input signal. The parameters have been rescaled to match the experimental conditions and the external input signal is added as a modulation to the Mach-Zehnder.



Fig. 5: (Top) NMSE prediction error in the Santa-Fe time series prediction for $\beta = 0.8$ and $\gamma = 0.45$ as a function of the phase ϕ . (Bottom) NMSE prediction error in the $\beta - \gamma$ plane for ϕ =-0.65 π .

A detailed numerical study allows for the search of the parameters leading to an optimum performance of this optical system with delay for RC purposes. The numerical study includes a truncation to 10 bits precision in the computations to mimic the experimental conditions. Figure 5 (top) shows the NMSE prediction error for β = 0.8 and γ = 0.45 as a function of the phase ϕ . The numerical results

agree with the experimental findings reported in Fig. 4 (bottom). Figure 5 (bottom) presents a summary of the numerical predictions for the NMSE prediction error around an optimum region of operation (ϕ =-0.65 π) in the β - γ plane.

Discussion and Concluding remarks

The prediction errors for the time-series prediction task reported in this contribution are comparable or even better than current state-ofthe-art approaches^{9,12}. The reasons behind the present improvement are twofold. First, the experiments are carried out with an optimum feedback strength, which can be estimated via numerical simulations. Second, the use of a multi-valued mask improves the prediction error for a time-series prediction task. We find a delicate balance between the number of amplitude levels allowed in the input mask and the finite Signal-to-Noise ratio of the experimental implementation.

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