Delayed electro-optic phase dynamics for ultra-fast Nonlinear Transient Computing

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Abstract—Dynamical systems have recently triggered various interests for their potential as efficient and powerful information processors. Among those recent breakthroughs, one finds *Reservoir Computing*, a brain inspired computational paradigm proposed in the early 2000 on the basis of neural network concepts. The approach is making use of the transient motion complexity developed in the high-dimensional phase space of a nonlinear dynamical system. The computed result is obtained from a linear read-out of that transient motion in the phase space, the motion being triggered by the proper injection of the input information which is thus driving the transient dynamics. Beyond this conceptual novel paradigm, hardware proofs of principle have even been successfully proposed recently, moreover with impressive computational capabilities. We will report on recent advances in such hardware implementation of *Nonlinear Transient Computing*, in which an ultra-fast electro-optic nonlinear delay oscillator have been used to demonstrate a physical unit capable of processing information with multi-10 GHz bandwidth capabilities.

1. Introduction

Brain-inspired computing principles have already been addressed in the 40s however mainly from the conceptual point of view, whereas our nowadays digital computers, the so-called Turing-Von Neumann machines, started to be physically implemented. After a fantastic development of those digital computing machines, up to nowadays with everywhere present digital processors from laptop to smart phones through super-computers, Moores'law has started to saturate. The main reasons are the closeness of nowadays technologies to physical limitations, e.g. in terms of surface heat dissipation (resulting in GHz processor speed limitation since 2005), in terms of density of transistors (related among others, to problematic probability of faulty individual devices during fabrication), and in terms of the control of parallelism complexity of digital architectures (problem to design efficient algorithms for multi-core parallel digital processors). Beyond these physical and technological limitations, one faces more and more high complexity scientific and technological challenges that can not be fully addressed, or can not be solved confidently, or can not be processed fast enough, by the available digital computers. From this current situation, alternative paradigms for more powerful novel computational machines are expected to be of strong importance for any future progress of our information technology society, not only from the conceptual point of view as it was essentially explored up to now, but also from the physical implementation issues. Brain-inspired approaches are offering obvious potential solutions inspired by the Nature, with many advantages such as fault tolerance, learning capabilities, and extremely complex problems resolution capability.

As already stated, the brain or its huge and complex structure of interconnected neurons, usually represents the straightforward architecture to be investigated for the discovery of novel computational paradigms. A typical and widely explored such paradigm is Recurrent Neural Networks (RNN). Essential to notice, are their intrinsic features such as complex dynamical network, thus highlighting the obvious central disciplines of nonlinear dynamics and complex systems sciences. In recently accomplished EU project, PHOCUS [1], dedicated to Reservoir Computing [2, 3] in photonic hardware a consortium essentially formed with nonlinear dynamics research groups, a surprising, but finally efficient approach was explored, consisting in the use of complex nonlinear delay dynamics, in place of the neural network dynamics. Conceptually, the idea was to make use of a known analogy between spatio-temporal dynamics, such as the one of a neural network, and a delay dynamical system (having also an infinite dimensional phase space). Beyond this concept, different groups succeeded in hardware demonstrations [4] of photonic Reservoir Computing [5, 6, 7, 8], moreover with unprecedented state of the art performances.

Following this research direction, we have investigated an ultra-fast electro-optic delay oscillator architecture, from which we were expecting to show Telecom bandwidth operation capability of photonic Reservoir Computing with potentially record processing speed, e.g. up to 1 million words per second for a spoken digit recognition task.

The paper is organized as follows: first we will describe the experimental setup and its operating parameters; then we will explain how it can be considered as a virtually emulated network of neurons to be used as a Reservoir in the standard Reservoir Computing framework; finally we will illustrate the processing, and its performances, when addressing through the setup a standard academic classification task known as spoken digit recognition. We will finally conclude with perspective and future evolution of this emerging delay dynamics based Reservoir Computing.

2. Experiment and modeling

Since our aim was to demonstration over 10-GHz bandwidth processing capability of photonic Reservoir Computing, an already available but recently designed ultra-fast electro-optic delay oscillator was chosen [9]. The broadband and highly controllable nonlinear dynamics setup was indeed recently proposed in the context of optical chaos communications, achieving state of the art distance, speed, and transmission quality for this physical layer encryption method based on chaotic motion and chaos synchronization [10].

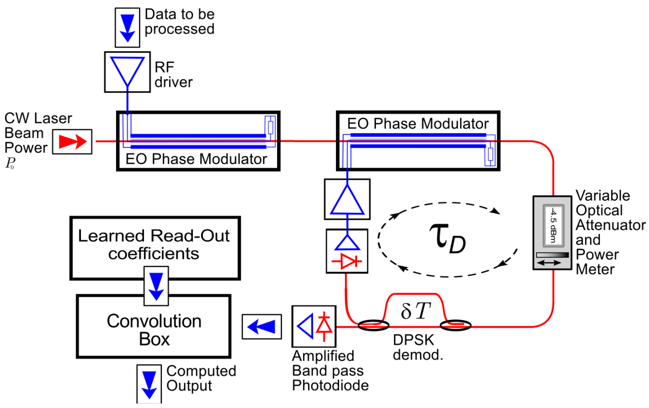

Figure 1: Electro-optic phase setup realizing a photonic Reservoir Processor

2.1. Electro-optic phase delay dynamics

The electro-optic phase setup with an optoelectronic delayed feedback loop is depicted in Fig.1. The closed feedback loop follows the typical optoelectronic chaos architectures [11], providing the "recurrent" character of the dynamics. The oscillator requires also an input to inject into it the information to be processed. This is fulfilled by an external phase modulator, which simply adds the information to the delayed self feedback. The delayed self feedback is performed through a second electro-optic phase modulator. The recurrent action of the Reservoir Computing concept is thus provided by the delayed optoelectronic feedback loop, which comprises:
(*i*) A length of fiber delaying the phase modulation carried by the laser light beam by a time shift τ_D;
(*ii*) A nonlinear function provided by the phase to intensity conversion obtained from an imbalanced passive fiber-based Mach-Zehnder -MZI- interferometer (actually consisting in a conventional differential phase shift keying -DPSK- telecom demodulator).
(*iii*) A photodiode converting the intensity fluctuations into an electronic signal with a sensitivity S;
(*iv*) A broadband Telecom RF driver with gain K to apply the electronic signal to the second phase modulator which is the one providing the recurrent feedback.
The slowest element in the feedback is typically the amplified photodiode having an electronic bandwidth of 13 GHz with a low cut-off around 30 kHz, both frequencies resulting in characteristic response time of τ and θ respectively, corresponding qualitatively to low-pass and high-pass filtering, respectively.

The main physical parameters used to adjust a "suitable" optoelectronic implementation of the Reservoir Computing approach are the following:
(*i*) The continuous wave optical power P_0 of the DFB Telecom laser diode (emitting at 1.5μm) allows for the weighting of the feedback, which practically corresponds to the adjustment of the spectral radius for the recurrent dynamics involved in the RC approach. Too large feedback levels lead to oscillatory or chaotic motions [9], which is not suited for RC processing since the fading memory property is not obtained. Too small values on the contrary makes the recurrence becoming meaningless in the RC processing. Optimal values corresponds empirically to a feedback gain slightly smaller than the one leading to the first bifurcation of the system stable fixed point (while increasing this gain from zero).
(*ii*) The laser wavelength λ combined to the fine tuning (within the accuracy of a fraction of the wavelength) of the MZI optical path difference -OPD- Δ (typically achieved via a heating wire rolled around one arm of the fiber-based MZI) allows to determine the non linearity profile involved in the delayed recurrence (or feedback). Setting the interference phase offset $\phi_0 = 2\pi\Delta/\lambda = \omega_0\,\delta T$ (where $\delta T = \Delta/c$ is the time unbalancing in the MZI) to zero modulo π leads to a locally parabolic nonlinear contribution, whereas $\pm\pi/2$ modulo π corresponds whether to a nearly linear recurrence, or a cubic one, depending on the phase modulation span issued from both feedback and information to be processed.
(*iii*) Since the normalized feedback level requires to be smaller than 1, if one aims at a large phase modulation span (of the order of π to access significantly nonlinear operation of the DPSK), this is obtained mainly through a proper amplification of the signal driving the modulation of the first phase modulator.

According to the previous setup description, the dynamical model ruling the evolution in time of our electro-optic phase Reservoir Computer reads as follows:

$$\frac{1}{\theta}\cdot\int_{t_0}^{t}\varphi(s)\,\mathrm{d}s + \tau\cdot\frac{\mathrm{d}\varphi}{\mathrm{d}t}(t) + \varphi(t) = \qquad (1)$$
$$\beta\left[\cos\phi_0 - \cos(\varphi_{\tau_D} + \varphi^m_{\tau_D} - \varphi_{(\tau_D+\delta T)} - \varphi^m_{(\tau_D+\delta T)} + \phi_0)\right],$$

where $\varphi(t)$ is the phase modulation performed by the internal feedback electro-optic modulator, whereas $\varphi^m(t)$ is the phase modulation issued from the electro-optic modulator injecting the external information to be processed. The notation φ_T stands for the signal delayed by the subscript time shift, i.e. $\varphi(t-\tau_D)$. The parameter β is the normalized gain of the delayed feedback term which is proportional to the laser optical power P_0. One could notice in Eq.(1) that the contribution of the integral could be neglected quantitatively since the time unbalancing δT is usually much faster than the integral characteristic time θ, which might simplify the numerical simulations.

When setting the external signal φ^m to zero, Eq.(1) describes the autonomous nonlinear non-local dynamics explored in [9, 12], and which were recently explored in these references for their rich and unusual dynamical feature issued by strongly spread multiple time phenomena $\theta \ll \tau_D \ll \delta T \ll \tau$ of the order of μs, 100 ns, 400 ps, and 10 ps respectively.

2.2. Delay dynamics emulating a network of virtual neurones

An RNN as typically referred to in many brain-inspired computing approaches, is a spatio-temporal dynamical system, which internal parameters have to be optimized through a learning procedure, so that the output response of the network enables the computation of the expected function of the input data. The original approach proposed within the PHOCUS project [1], is to make use of a known analogy between delay dynamics and spatio-temporal ones [13] to emulate a virtual network of neurons, or more precisely its complex phase space capacity, with a nonlinear delay dynamics. A significant practical advantage of the proposal is related to the fact that delay dynamics are already well known to have well controlled experimental implementations in photonic, moreover benefiting from typical Telecom bandwidth operation capabilities. Additionally to the very attractive interest for a possible dedicated hardware for brain-inspired computer, one could also dream along this line about ultra-fast processing capabilities thanks to the available broadband photonic Telecom technology.

The practical solution enabling this virtual emulation of a network through a delay dynamics, precisely involves a Telecom technology concept known as TDM, time division multiplexing. As shown in Fig.2, a virtual space is emulated along the fast time scale motifs filling the time interval defined by the long delay τ_D. Virtual neurons are then corresponding to time positions within a time delay interval, the number of such neurons being related to the number of time motifs of the order of the fastest time scale, τ,

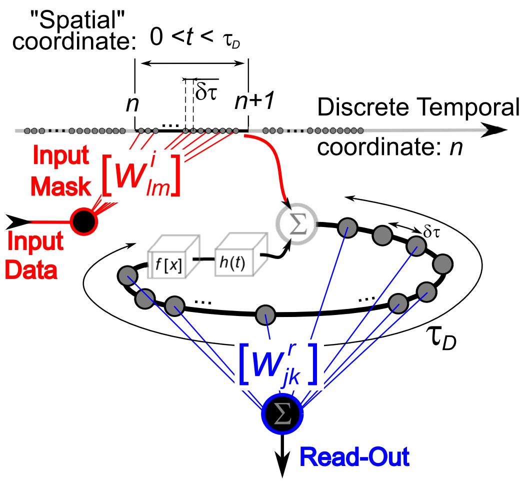

Figure 2: Virtual space in delay dynamics emulating neurons along the time delay interval in the feedback loop. Two adjacent virtual neurons are separated by $\delta\tau$.

which can be used to fill an entire delay interval. This number of neurons for a delay systems finds a nice match with the known attractor dimensions, however in chaotic regime, which scale precisely with the ratio τ_D/τ. Addressing each of these neurons filling a time delay interval, is performed through time division multiplexing. An elementary input sample of information is sent to each of these neurons with a specific coupling coefficient. The next sample will be spread through the same method, but one time delay after, with the same set of coefficients (defined through a so-called input mask) attributed to each of the virtual neurons. This method of information injection into the virtual network corresponds to the well known input layer of classical neural network computing methods.

A similar but slightly different method is used to extract the output result from the photonic RC response (see [4, 5] for more details). The continuous time response of the delay dynamics with respect to the input information flow is first sampled. The samples are then convolved with a sequence of learned coefficients to provide the answer to the initial problem. These coefficients are obtained through a ridge regression procedure utilizing a set of known couples of (*RC response, answer or calculation result*), see the Read-Out matrix W^r_{jk} in Fig.2.

3. Testing the computational power

In order to compare the computational capability of our broadband electro-optic phase delay dynamics, we reproduced a classification test which has already been successfully conducted for the first demonstration of photonic Reservoir Computing [5].

3.1. Spoken Digit Recognition task

The test consists in the recognition of digits between 0 and 9, within a standard database of 500 such digits. The digits are pronounced by 5 different female speakers uttering ten times the ten digits. We refer to the previous literature for more details about this test [14, 4, 5].
The essential of the photonic hardware processing consists in the injection of 500 signals corresponding to each of the mask-encoded digits, and then the recording by an ultra-fast digital scope of each transient response from the EO phase delay dynamics (the Reservoir). The learning (ridge regression from a subset of the recorded 500 responses) and the testing (convolution with the learned coefficients, performed on the complementary subset of the Reservoir responses) were operations performed off-line on a standard computer. Through learning algorithms are for the moment necessarily implemented in a standard digital computer, the Read-Out operation can in principle be designed physically, thus allowing a real time ultra fast recognition.

3.2. Speed and Word-Error-Rate performance

In order to process all the 500 digits, we have followed a similar procedure with respect to the one described in [5], excepting for the following issues:
- The total delay resulting essentially in the interconnected pigtails of the different photonic components, was measured to be 63.33 ns ±8 ps. This suggested to slow down the motion with an additional low pass filter with 566 MHz frequency cut-off, resulting in $\tau \simeq 284$ ps, which arbitrarily defines as in [4] a neuron spacing $\delta\tau = \tau/5 \simeq 56.8$ ps (thus imposing the input sampling frequency of the mask-encoded data to 17.6 GHz). In order to have a comparable size in processing neurons (of the order of 400), 3 unmasked input data were chosen to fit the time delay duration, resulting in 371 neurons per mask-encoded input, or 1113 neurons within one time delay.
- The time varying response for the 371 virtual neurons was then recorded at 80 GS/s by a real time digital scope, thus allowing for the choice among 5 samples in the Read-Out processing.

With these settings, the average duration of a spoken digit being around 60 original samples (each of which being spread over the 371 virtual neurons), the average duration required for each digit processing by our photonic EO phase Reservoir amounts to ca. 1.3 μs. This corresponds to a processing rate close to one million digit recognized per second.
The word error rate is slightly degraded compared to previous results, however staying at a very good level with a best operating point slightly below 1%.

4. Conclusion

We have proposed an electro-optic phase delay dynamic which can be used as a photonic RC. The Telecom bandwidth capability of the setup could allow for ultra-fast information processing, with the efficiency and computational power capability provided by RC. Spoken Digit Recognition task has been implemented, demonstrating potential recognition close to 1 million words per second, with reasonably good word error rate below 1%.

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