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[Invited Talk]

All-optical Reservoir Computing in Networks of Lasers

D. Brunner and I. Fischer

Institute for Cross-Disciplinary Physics and Complex Systems (IFISC),
University of the Balearic Islands, 07122 Palma de Mallorca, Spain
Email: dbrunner@ifisc.uib-csic.es, ingo@ifisc.uib-csic.es

Abstract—During the last decade, the novel information processing scheme of Reservoir Computing (RC) demonstrated exceptional performance when applied to challenging computational tasks. What makes RC unique within neuro-inspired information processing is its suitability for hardware implementation in analog and photonic systems. After highly successful realizations in delay systems, the scheme is now extended to other types of photonic networks. We will report on the latest advances made in the implementation of RC in spatially extended networks of semiconductor lasers. When successful, such systems have the potential of all-optical, standalone information processing with massive parallelism at 10s of GHz processing bandwidths.

1. Introduction

The Reservoir Computing (RC) [1] or Liquid state Machine (LSM) [2] concept was introduced around a decade ago. It is based on neuro-inspired information processing, utilizing complex and high-dimensional transient dynamics induced into a complex network of nonlinear nodes by the to be processed information.

The scheme is illustrated in Fig. 1. Information is injected from input nodes into a network (often random) of nonlinear nodes, the Reservoir, according to randomly assigned injection weights. The information induces complex and high-dimensional transient responses of the reservoir nodes. Owing to this dimensionality expansions, theoretically it is possible to solve any computational problem by simply creating a linearly weighted sum of the Reservoir's node states. Following standard machine learning training procedures, the linear readout weights are adjusted in order to perform the desired task by using available example data.

Emulations on standard, electronic von Neumann machines demonstrated state-of-the-art performance when applying RC to complex benchmark tests. Among typical performance evaluations tasks are the classification of spoken digits, the prediction of chaotic timeseries, radar and wireless communication signal processing and many more. Such emulations on von Neumann machines, however, significantly reduce the appeal of RC: the transient-dynamics of each network node has to be computed in a serial fashion. Therefore, the overall information processing bandwidth is significantly reduced.

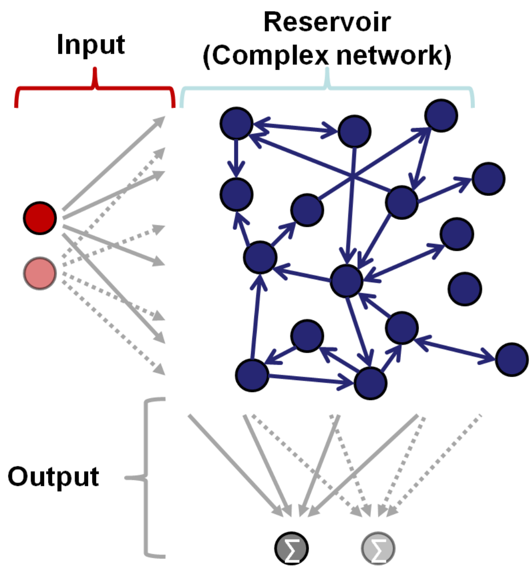

Figure 1: Schematic illustration of the RC concept. Information enters the system via the red input nodes, from where it is injected into the network of nonlinear nodes (blue) according to random connections weights. The systems output (gray nodes) are created via a linearly weighted sum of the individual reservoir nodes. Using standard learning procedures, individual weights of the linearly sum are adjusted in order to perform the desired operation.

Even stronger weighs the impact such an emulation has on the parallel computation capability of RC. The theoretical framework of RC makes the concept inherently parallel, allowing for massive parallelism in information processing. When implementing the scheme in a single core, serial von Neumann processor, this possibility is lost. Only implementations of RC in nonlinear networks allows for full exploitation of the concepts merits.

2. Harware implementations of RC

Essential to RC is a significant simplification when compared to previous machine-learning algorithms. Consequently, hardware implementations in physical complex networks became realistic. Utilizing the high-dimensional space of delay coupled systems, RC was demonstrated in electronic [3], opto-electronics [4, 5] and all-optical [6, 8] systems.

These hardware implementations were significant for the success of the field. Following the delay-approach, it is possible to define a ring-like network in which most parameters can be controlled by having access to a single hardware element only. As such, experimental conditions can be accurately controlled and fundamental properties of hardware-implemented RC could be evaluated for the first time. Furthermore, the implementation's simplicity allowed to implement neuro-inspired information processing in photonic hardware while profiting from photonics' high dynamical bandwidths [7]. Demonstrating the same computational concept either using the nonlinearity of a simple transistor, a Mach-Zehnder modulator or photonic-semiconductor devices (SOA, laser diode) also proved the versatility of the concept. While numerical emulations were largely restricted to threshold nonlinearities, e.g. piecewise step-function, these experiments demonstrated that the exact type of nonlinearity appears to play a minor role in the implementation.

3. Reservoir Computing based on spatially extended all-optical networks

An important step for the field is extending hardware implementations of RC to spatially extended networks. Such systems will allow for fundamental extensions of the concept, however they come with significant challenges. As can be seen from Fig. 1, the network of nonlinear elements features a random connectivity, something which the circular networks of delay elements can only approximate. Furthermore, delay-implemented reservoirs' bandwidth is inherently reduced by the number of emulated nodes, presenting a significant reduction of processing bandwidth for the typical Reservoir of a few tens to hundreds of nodes.

A schematic illustration of our experimental setup is shown in Fig. 2. The network of nonlinear elements is based on an array of Vertical-Cavity Surface-Emitting lasers (VCSELs). Taking profit of the accurate periodicity of such semiconductor devices, an network of lasers is formed optically by utilizing the diffraction-pattern of a Diffractive-Optical-Element (DOE). Upon back-reflection from the SLM (therefore passing the DOE twice), the DOE creates diffractive orders of each laser's emission, which are imaged on top of the 24 neighboring lasers for each laser. Therefore, in our system we realized a network with nearest and next-nearest neighbor coupling.

Advantageous to multi-hardware node systems is that injection and readout procedures do not require a dynamic modulation addressing individual nodes. In our spatially extended optical system, realizing a heterogeneous injection of information into different Reservoir nodes is provided by the imaging properties in optics, combined with the naturally occurring diversity of the individual hardware nodes. Therefore, each node will react differently to the injected information, establishing the dimension-expansion required by the machine-learning concept, Information is

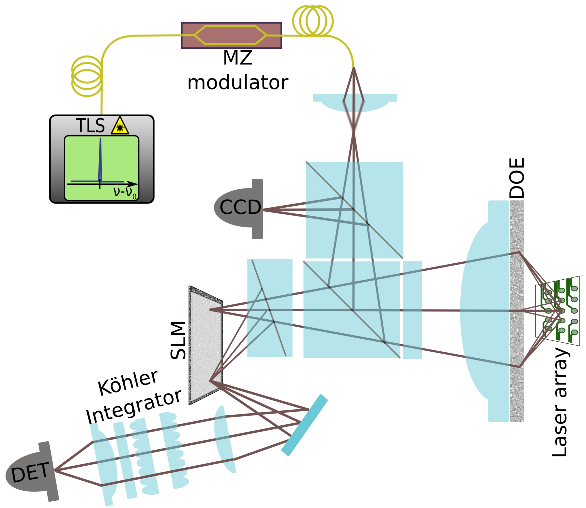

Figure 2: Schematic illustration of an all-optical implementation of RC in an array of lasers. Using a diffractive-optical element (DOE) and the reflection of a spatial-light-modulator (SLM), a network is formed between the lasers of a VCSEL array. A Rochon prism creates two images of the network on the SLM, were the lower image is utilized for implementing the Reservoirs readout weights. Using a Köhler-integrator, a spatial integration of the linearly scaled network state is created, realizing an all-optical classifier. All-optical information injection is realized via an external tuneable laser (TLS), which is intensity modulated via a Mach-Zehnder (MZ) modulator.

encoded in the optical injection using a Mach-Zehnder (MZ) intensity modulator.

Using a Rochon-prism, a second image of the array is created on the SLM. The gray-scale of the SLM is then utilized for applying readout-weights to the individual network nodes. A standard beam homogenizer, a Köhler-integrator, creates a small area ($\approx 50 \times 50\,\mu$m), in which the optical intensity of the array, scaled by the readout wights, is integrated.

4. Properties of the all-optical, multi-node reservoir

Based on our experimental setup, we start to evaluate the boundary conditions for RC. The first essential step is the successful formation of the Reservoir. In Fig. 3 a), we show the PI-characteristics of our 8×8 laser array. A strong indication for self-feedback and coupling to other lasers is the reduction of the lasing threshold. This feature can be identified in the panels of Fig. 3 b). Panels in Fig. 3 b) show the PI-characteristics for lasers (5,4), (5,5) and (5,6) for the solitary devices (red) or when implemented in the network (black). Here, we follow the notation of (Row, Column) for addressing individual laser diodes. One can identify a general trend: laser located in the center of the network experience a significantly larger threshold reduction than lasers located at its fringes. This is caused by

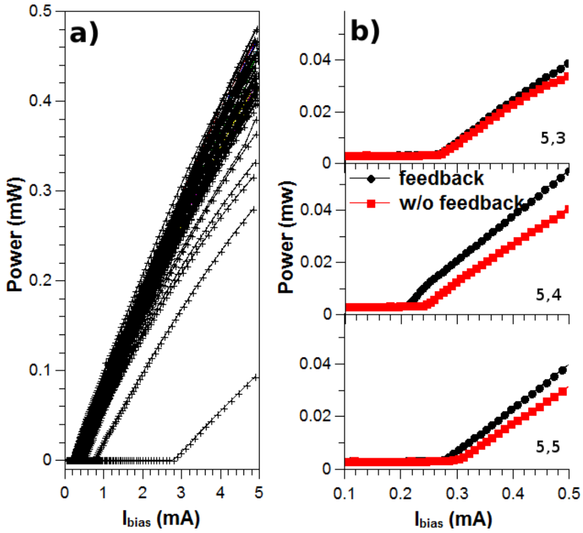

Figure 3: Fundamental characterization of the laser network. Panel a) shows the individual PI-curves for all lasers of the 8x8 array. Panel b) shows the threshold reduction of selected lasers caused by the coupling in the network.

spherical aberrations present in our imaging system. Therefore, it is not a fundamental limitation and the problem can be resolved by simple means like a tailored imaging lens or a modified resonator structure.

Information injection into the Reservoir is the next requirement for information processing. In our injection scheme, we lock the network lasers to the injection laser. By selecting the injection's polarization orthogonal to the detection, we obtain an inverted locking scheme. It allows us to correlate intensity modulations in the detection directly to the response of the network, ruling out strong crosstalk from the injection source. Low crosstalk between injection and the classifier is critical since it lacks nonlinearity and hence can not aid the information processing. Here, we achieve a modulation amplitude between 50 and 80 % of the Reservoir's output power. The information injection rate is determined by the time-delay introduced by the optical coupling of the individual lasers, which in our setup amounts to $\approx$1.2 ns.

The final step in the computation is the application of a scaling factor to the individual reservoir nodes and to detect the optical response of the system. Based on the SLM, we can scale the optical intensity of each Reservoir node with a contrast between 50 and 100:1.

Our setup therefore provides all fundamental building-blocks for an all optical Reservoir Computer. All-optical data injection, the optical network of lasers and the optical classifier are all implemented in hardware. Our system therefore has significant potential for being the first RC including all essential parts and components in hardware. Such a system would be able to process complex data at high speed, in our case $\approx$700 MHz, all optically. Small modifications to the setup would also allow for parallel information processing.

Finally, it is important to mention that the current scheme exclusively relies on device-inherent properties. Therefore, no part of the setup would require dynamic addressing or modulation. All sections are exclusively operated with DC-signals, possibly allowing for highly-integrated and hardware-efficient implementations in the future.

As the final step, we will report on the progress of implementing RC in the presented optical system.

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