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PHOTONIC RESERVOIR COMPUTING FOR ENERGY EFFICIENT AND VERSATILE MACHINE LEARNING APPLICATION

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Abstract: Time-multiplexed reservoir computing is a machine learning concept which can be realised in photonic hardware systems using only one physical node. The concept can be used for various problems, ranging from classification problems to time-series prediction tasks, while being fast and energy efficient. Here, a theoretical analysis of a reservoir computer realised via delay-coupled semiconductor lasers is presented and the role of the internal system time-scales and the bifurcation structure is discussed. It is further shown that optimal performance can be reached by tailoring the coupling delays to the specific memory requirements of the given task.

Keywords: reservoir computing, time-multiplexing, delay-coupled lasers, memory capacity

The ever increasing demand to analyse large amounts of data has tremendously driven the field of machine learning techniques. The most common and very fast developing concepts are deep neural networks which are trained by error back-propagation. This deep learning boom has yielded impressive results, including applications from cancer detection (Tran et al. 2021) to galaxy classification (de Diego et al. 2020). However, in terms of energy efficiency the concept needs to be improved as, for example, next-generation models like GPT-3 consume thousands of kilowatt-hours (Wu et al. 2022).

One idea to reduce the energy consumption for analog computing systems is reservoir computing (RC), a machine learning scheme that draws inspiration from the human brain (Maass et al. 2002) and the computational abilities of dynamical systems (Jaeger 2001). Compared to deep neural networks that are formed by many layers with a multitude of nodes, the RC paradigm has a much more efficient training procedure and a very promising advantage: it can be implemented in various physical hardware systems because only the readout connections have to be trained to fulfil a computing task. This is a simplification that demands a higher system dimension, but yields nearly instantaneous training times. All physical systems that perform a nonlinear transformation on an input signal are candidates for a realisation. One example of hardware systems are optical reservoirs which have the additional advantage of fast processing speeds. In the past decades, it was demonstrated that photonic hardware systems can effectively solve complex tasks with low energy costs (Antonik et al. 2016; Du et al. 2017; Shi et al. 2022; Porte et al. 2021).

Time-delay based reservoir computing (Appeltant et al. 2011) is a specific implementation of RC where only a single physical node is needed and, in contrast to the spatially extended networks, the information is multiplexed in time and injected into so called virtual nodes. The concept has already been investigated and experimentally demonstrated by various groups. It was, for example, shown to work for time-series prediction (Bueno et al. 2017; Kuriki et al. 2018), equalisation of nonlinearly distorted signals (Argyris et al. 2020) and fast word recognition (Larger et al. 2017). For more details please see the recent reviews (Brunner et al. 2019; van der Sande et al. 2017; Tanaka et al. 2019; Nakajima et al. 2021).

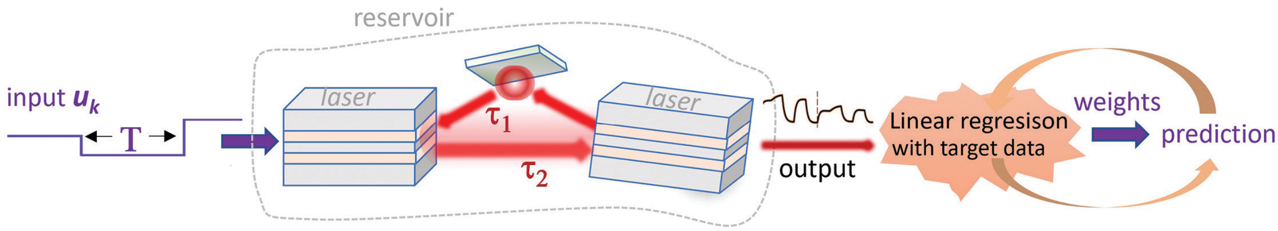

Figure 1: Photonic delay-based RC setup consisting of two lasers coupled with delays τ_1 and τ_2. The inputs u_k are fed into the laser, each for one clock-cycle T. The target (task) is a future step of the input time series and the prediction is calculated by multiplying the sampled laser output with the weights that are determined during training via linear regression.

In this paper, the investigation is performed with a time-delay based RC setup, where two delay-coupled lasers are used as physical nodes together with a time-multiplexed input scheme. For this system, only the weights for the weighted sum of the laser output entries are trained via one single linear regression step. Semiconductor lasers have the additional advantage of being compatible with a chip-based solution. Figure 1 shows the setup with two asymmetrically coupled lasers, together with the training scheme for the case that a time sequence of inputs u_k is optically injected and the next step is to be predicted by the RC. For the delay-based RC setup, the usual spatial-multiplexing within a network is replaced by time-multiplexing, where different points in time of the input are weighted via a modulation within one clock cycle, i.e. via multiplication with a mask signal (Köster 2023; Hülser et al. 2023; Röhm et al. 2019). By performing a bifurcation analysis as a function of the system parameters, possible ways to improve the performance of the delay-coupled laser setup can be found. A very efficient way is the tuning of the internal coupling-delay times (Hülser et al. 2022). While many other purely computational methods for time-series prediction (e.g. weather data) have been around for a long time (Jaurigue & Lüdge 2022), the idea behind this research on photonic realisations is the possibility for a fast and energy efficient solution. The inherent memory of the delay-based RC setup is well suited to perform time-series prediction on dynamically complex or even chaotic time-series data u_k. To evaluate the results, three different examples for u_k (i.e. NARMA10, Lorenz-X and Mackey-Glass) were chosen (Hülser et al. 2023) and the prediction performance one step into the future as a function of the two delay-times was determined (Figure 2, three leftmost panels). Because the delayed terms strongly increase the dimension of the phase space, the dynamical system response to perturbations can be very complex (Hausen et al. 2021) and a thorough bifurcation analysis is needed to detect parameter regions for stable operation. This is needed to guarantee a consistent response of the laser to the injected data. Within the blue regions in Figure 2 the RC computing performance is best. Nevertheless, the good performing regions are interrupted by regions of bad performance which, however, strongly depend on the delay-times and also on the task (compare the three left panels of Figure 2). Thus, a thorough analysis of the system's dynamics and the task requirements is always necessary when dealing with nonlinear reservoir computing systems.

The memory properties of a delay-based RC setup can be quantified by the linear memory capacity that measures how well different past inputs can be remembered. It is determined numerically by training the reservoir to remember an input from n-steps into the past and then summing the values of the performance over n. Unfortunately, the correlation with the performance on a specific time-series prediction task is not straightforward. This can be seen by comparing the task-independent memory capacity (Figure 2, right) with the performance of the setup after training for the three different time-series prediction tasks (Figure 2, left) where a very different dependence on the system parameters can be seen. While an analytic connection between the linear memory capacity of an RC system and the linear system response of the underlying physical system can be found and opens the possibilities to predict parameters for good memory properties of the reservoir (Köster et al. 2021; Köster et al. 2022), the connection to a specific task is more complex. By analysing the series expansion of the tasks, it could be shown that the performance can be predicted if both the memory properties and the expansion coefficients are known (Hülser et al. 2023).

The theoretical results show that an all-optical RC setup with delayed coupling can be effectively trained and used for time-series prediction applications. Nevertheless, attention has to be paid to the dynamic time-scales governing the optical setup. Resonances between input clock-cycle T and delay time τ can be detrimental to the prediction performance. Further, if the nonlinear properties of the physical system are to be used in an optimal way,

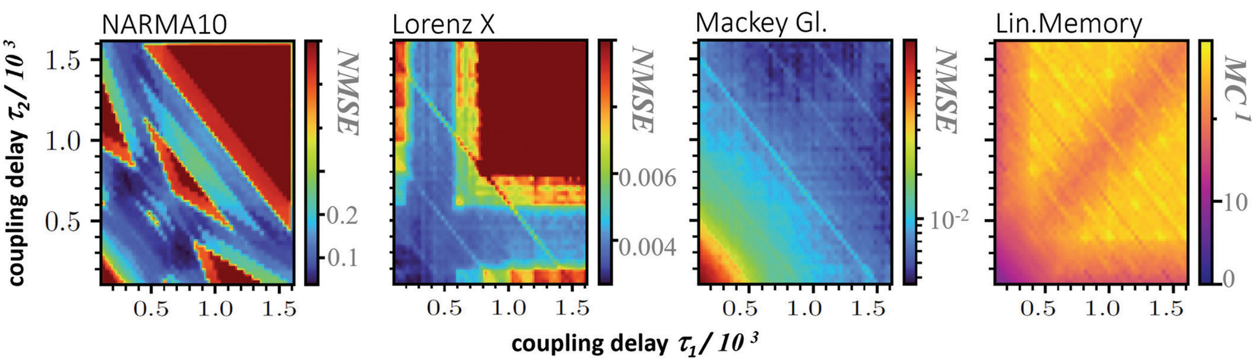

Figure 2: Normalised mean square error (NMSE) plotted as a color code as a function of the two coupling delay times τ_1 and τ_2 of the delay-based RC setup shown in Figure 1. From left to right the one-step prediction task of NARM10, Lorenz X and Mackey Glass are shown (see Hülser et al. 2023 for details on the numerical method). The rightmost panel depicts the linear memory capacity in the same parameter space.

the sampling rate of the time-multiplexed output has to match the internal relaxation time-scale of the dynamical system (Hülser et al. 2022; Köster 2023), and the specific memory requirements of the given task have to be included via tailoring the delay values (Jaurigue et al. 2022; Hülser et al. 2023).

Conflict of interest

The author declares no conflict of interest.

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