Phase modulation improves performance of delay-based reservoir computing with semiconductor lasers

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In photonic reservoir computing, semiconductor lasers with delayed feedback can be used to efficiently solve difficult and time-consuming problems. We show numerically that the performance depends heavily on how the data is modulated on the optical input signal [1]. We compare different input configurations for injecting the input signal into the reservoir and evaluate their performance on the one-step ahead Santa Fe prediction task. Based on simulations, we show that better performance can be achieved by using an unbalanced Mach-Zehnder modulator, which modulates both intensity and phase, as compared to a balanced Mach-Zehnder modulator, which only modulates the intensity. This implies that modulating the phase of the injected field is essential to get good computational performance in this type of reservoir computers. We also observe a further improvement in performance when using a phase modulator alone. We can thus conclude that using only a phase modulator as input configuration, with well-chosen modulation amplitude, is ideal for solving tasks using semiconductor lasers with delay, both performance-wise as well as in simplicity of implementation.

Introduction

In our current technological society, we are becoming increasingly able to process and analyze information using machine learning. The concept of reservoir computing (RC) within this machine learning field offers a simple, yet powerful technique to use recurrent networks for computing. RC systems have shown good performance in various benchmark tasks. An RC system consists of a large recurrent neural network with fixed interconnections. Its topology can be described in three separate components: an input layer, the reservoir, and an output layer. In the input layer, the data is injected into the system and is sent to the reservoir, which consists of a recurrently connected network of non-linear nodes. The processed information is then sent to the output layer, where the output weights are optimized to match the output with a corresponding target output. The optimization of weights, and thus the training phase, occurs only in the output layer, whereas the internal weights of the reservoir itself are not altered. This makes training much more straightforward compared to other artificial neural networks and simplifies RC in its implementation. Using photonics for implementing RC offers several advantages, ranging from a low-energy consumption, high-speed performance and the possibility of high inherent parallelism [2,3]. The injection of input data into this reservoir can be performed via several methods. The input data can e.g. be injected electronically. In this work, however, we will focus on optically injected data, which has the advantage of allowing higher data injection rates. This latter method can be performed by modulating the phase of the injected electric field by using a phase modulator or by modulating the amplitude of the electric field. In this work, we numerically investigate the effect of the optical data injection configurations on the performance of delay-based reservoir computing system [1].

Numerical implementation of delay-based reservoir computing

RC using semiconductor lasers with delayed feedback relies on a time-multiplexing approach to implement the reservoir. This delay-based technique has been implemented in several types of electronic or photonic reservoirs. Fig. 1 shows the topology of a photonic delay-based RC using a single mode semiconductor laser as non-linear node, which will be studied in this paper, and consists of an input layer, reservoir and output layer.

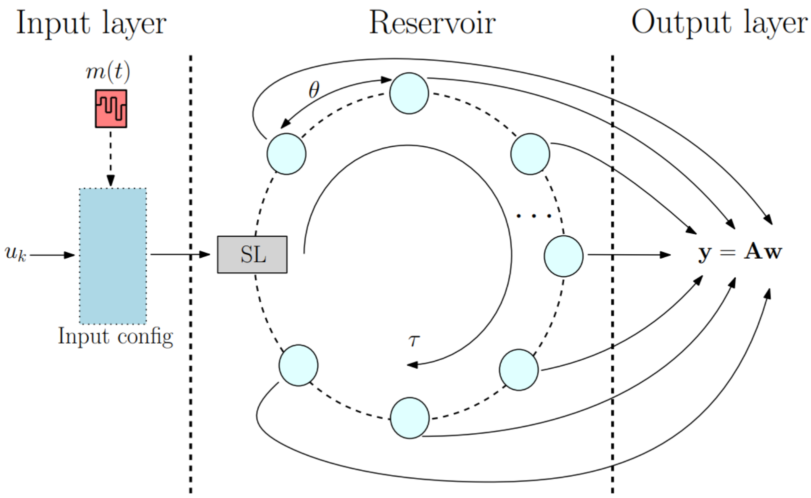

*Figure 1. Illustration of a delay-based RC system using a semiconductor laser (SL), with input data u_k, preprocessing mask m(t), node separation θ and delay time τ . The light blue circles represent the virtual nodes and the output layer is defined by the reservoir output **A** and output weights **w**.*

We use the intensity of the nodes, which are measured by sampling the output of the reservoir with a time separation θ. We can find the output weights **w** corresponding to the *N* nodes of the reservoir in the training phase. In order to achieve this, we use the output of the RC system **A**, which represents the node responses to the training input data, and the expected target data $\mathbf{y}^{\text{train}}$. In practice, the weights **w** can be retrieved by calculating $\mathbf{w} = \mathbf{A}^{\dagger}\mathbf{y}^{\text{train}}$, where † denotes the pseudo-inverse. In the input layer, we optically inject the discrete input data u_k, with k the index of the data sample, via an input configuration which we will vary in this work. Due to the time-multiplexing, we need to make use of a preprocessing mask m(t) before injecting the input data into the reservoir. The delay-based RC system with a single-mode semiconductor laser as non-linear node, can be accurately modeled using rate-equations [4]

$$\frac{dE(t)}{dt} = \frac{1}{2}(1+i\alpha)\xi n(t)\,E(t) + \eta E(t-\tau)e^{-i\Omega_0\tau} + \tilde{F}_\beta + \mu E_{inj}(t)$$
$$\frac{dn(t)}{dt} = \Delta J - \frac{n(t)}{\tau_c} - \left[g + \xi n(t)\right]\left|E(t)\right|^2,$$

where E(t) and n(t) are the complex valued electric field of the laser and the excess amount of available carriers (both dimensionless). α represents the linewidth enhancement factor, and ξ and g the differential gain and threshold gain. Parameters η and μ are the feedback rate and the injection rate. ΔJ represents the excess pump current rate, and is defined as $\Delta J = I_{thr}\Delta I/e$, where I_{thr} is the threshold pump current, e the elementary charge and ΔI the dimensionless pump current excess, $\Delta I = (I - I_{thr})/I_{thr}$. We use a single feedback phase, which is not varied in our work, $\Omega_0 \tau = 0$. $F_{\beta}^{\sim}$ represents complex Gaussian white noise to simulate the spontaneous emission noise strength. $F^{\sim}_{\beta}$ has a zero mean and autocorrelation equal to $< F^{\sim}(t)F^{\sim}(t')^{*} >= \beta/\tau_c \, \delta(t - t')$, where β controls the spontaneous emission noise and where τ_c is the carrier lifetime. Furthermore, the input data is injected through an optical input signal $E_{inj}(t)$ with the same wavelength as the free running laser, i.e. the injection frequency detuning is therefore equal to zero and not varied in this work. Following previous work in Ref. [5] we have chosen a value of 20 ps as the standard value for the node separation. In order to simulate the injection of data in the rate-equations, we specify the term $E_{inj}(t)$. For the unbalanced MZM $E_{inj}(t) \propto (1+e^{\,iB_{MZM}(t)})$, for the balanced MZM $E_{inj}(t) \propto (e^{iB_{MZM}(t)/2} + e^{-iB_{MZM}(t)/2})$, for the balanced MZM combined with PM $E_{inj}(t) \propto (e^{iB_{MZM}(t)/2} + e^{-iB_{MZM}(t)/2})e^{iB_{PM}(t)}$ and for the PM $E_{inj}(t) \propto e^{iB_{PM}(t)}$. The terms $B_j(t)$ ($j \in \{MZM, PM\}$) represent the masked time-dependent modulator signal which is used as input for the different input configurations of the RC system. We define the modulator signal $B_j(t)$, corresponding to input configuration j, from the masked data signal $S_j(t)$ using an amplitude A_j and bias Φ_j, $B_j(t) = A_j \, S_j(t) + \boldsymbol{\phi}_j$. In order to compare our results for tasks which have different ranges for their input data, we will introduce in our discussions the range of B_j, marked by ΔB_j. For the simulations of our delay-based RC system we numerically integrate the rate-equations [1].

Numerical results: Santa Fe time-series prediction task

In order to compare the performance of the different input configurations, we use a one-step ahead time-series prediction task. The input dataset used for this task is the Santa Fe dataset, which consists of data points sampled from a far-IR laser in a chaotic regime. The goal is to find the input configuration which results in the lowest error, and thus the best performance for this particular task. The performance is quantified by the NMSE (normalized mean square error), where typical values for the NMSE for the Santa Fe one-step ahead predictions via simulations of RC systems are around 0.01. We have taken 3000 data samples from the discrete Santa Fe dataset, u_k^{train} , where $k \in \{1,..., 3000\}$, as the training set in the RC system. As test set u_k^{test} , we have taken 1000 different data samples. We have repeated each numerical experiment 10 times, from which we calculate the average NMSE and its standard deviation (shown as error bars). If we consider a balanced MZM as input configuration, we find an NMSE = 0.134 ± 0.044, and if we use an unbalanced MZM, NMSE = 0.019 ± 0.0047. This result is in agreement with typical NMSE values found in literature. This is shown in Fig. 2, where we show the NMSE versus the total range of the phase modulator signal ΔB_{PM} for different input configurations. In this figure, we have indicated the performance of the (un)balanced MZM as a horizontal line. We also observe in this figure that, for the input configuration consisting of a PM and a balanced MZM, the NMSE initially decreases when increasing ΔB_{PM}, reaches an optimal point (with lowest NMSE) and again increases for larger ΔB_{PM}.

As we achieve a large improvement by adding a phase modulator, the question can be raised whether an MZM is required at all to obtain good RC performance. Ultimately, this allows for a simpler input configuration that only uses a phase modulator. We observe in Fig. 2 that the input configuration where only a PM is used results in the best mean

NMSE. This shows that replacing the MZM with a PM for the input configuration, and thus reducing the complexity of the input system, an improved performance can be achieved. We observe that the lowest NMSE values occur for input configurations with PMs around the broad range of $\Delta B_{PM} = \pi/2$ to π. Therefore, we achieve an improvement within this large ΔB_{PM} range. This optimal NMSE can be explained by two factors. For small ΔB_{PM} (around $\pi/4$), the system is limited by noise, so that it becomes difficult for the system to distinguish noise from different sublevel mask values. For large ΔB_{PM}, the phase modulated signal will stand to wrap on itself. Both of these phenomena will have a negative effect on the achieved performance and explain the existence of the optimal range in the modulator signal range ΔB_{PM}.

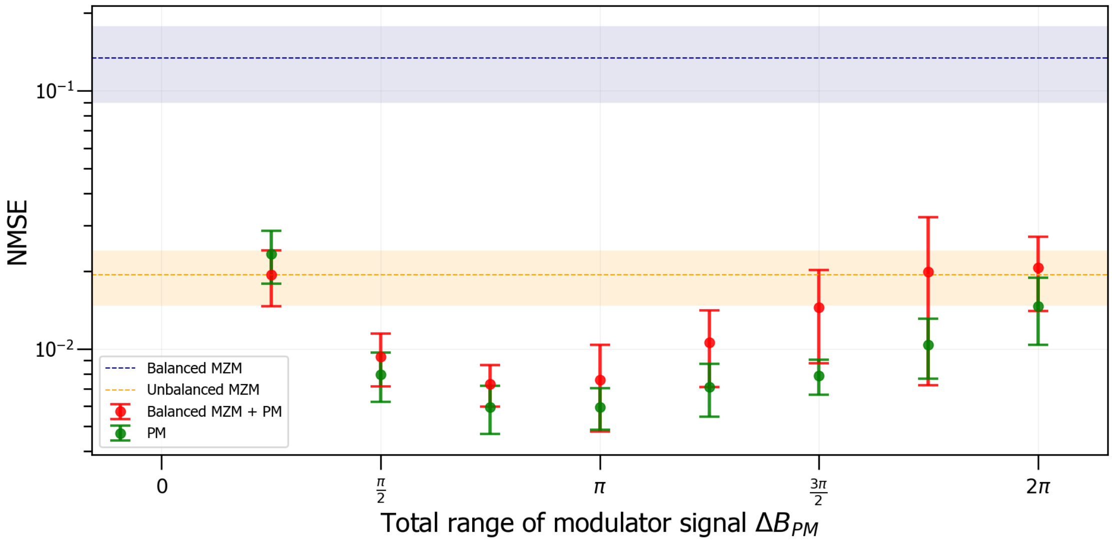

Figure 2. NMSE in function of the total range ΔB_{PM} of the phase modulator (PM) signal for one-step ahead prediction of Santa Fe data for different input configurations, showing improved performance when a PM is used.

Conclusion

We have numerically investigated the effect of modulating the phase when optically injecting data, with the goal of improving delay-based reservoir computing with semiconductor lasers. Using a phase modulator to inject the signal into the reservoir, resulted in an improved performance compared to literature. We therefore conclude that modulating the injected signal's phase increases the performance of optical RC for the one-step ahead prediction Santa Fe task.

References

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