Phase Modulation of the Input Signal Improves Performance of Reservoir Computing

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***Abstract*—In reservoir computing, semiconductor lasers with delayed feedback can efficiently solve difficult and time-consuming problems. The input data is optically injected into the laser. We show numerically that far better performance is observed using phase modulation of the injected field rather than intensity modulation.**

Keywords—reservoir computing, semiconductor lasers, feedback, optical injection, phase modulation

I. Introduction

Reservoir computing (RC) is a simple, yet powerful technique to use recurrent networks for computing. RC systems have shown good performance in various benchmark tasks, such as speech recognition, non-linear channel equalization or time-series predictions. Interesting implementations of RC systems can be found in the emerging field of neuromorphic photonics. The advantages of using photonic systems are abundant, ranging from a low-energy consumption, high-speed performance and the possibility of high inherent parallelism [1,2].

Here, we focus on a single mode semiconductor laser with delay-based RC [3-9]. The injection of input data into this reservoir can be performed via several methods. The input data can e.g. be injected electronically by direct modulation of the injection current, but we will focus exclusively on optically injected data, which has the advantage of allowing higher data injection rates. Information can be encoded on the injected optical carrier by modulating the phase of the injected electric field by using a phase modulator or by modulating the amplitude of the electric field. In literature, this is most often done using a Mach-Zehnder modulator (MZM) either balanced or unbalanced. Although, using either a balanced or unbalanced MZM will have an effect on the final performance of RC, its influence on RC performance has not yet been studied and compared in detail. In this work, we numerically investigate the effect of different schemes of optical data injection on the performance of delay-based reservoir computing system. Specifically, we compare modulation schemes consisting of a single (un)balanced MZM, an (un)balanced MZM combined with a phase modulator (PM) and a single PM.

II. RESULTS

For the numerical simulations, we have used standard Lang-Kobayashi rate equations for a single-mode semiconductor laser with delayed feedback taking into account optical injection with zero detuning. The optical injection term is altered for the different types of modulation. In the case of a balanced MZM, only the intensity of the injected field is modulated with the input data. In the case of a single PM, only the phase of the injected field will carry the input data. When the input data is modulated using an unbalanced MZM both the intensity and the phase will carry the same data signal. To be able to have a different modulation on the intensity and on the phase, we have also combined the (un)balanced MZM with a PM.

A. Benchmark task

The performance for the different optical input configurations is quantified by a one-step ahead time-series prediction as benchmark task. The used dataset for this prediction is the Santa Fe dataset, which consists of 9093 data points sampled from a chaotic far-IR laser. As a measure for the performance, we use the normalised mean square error (NMSE) between the predicted output using the delay-based RC system and the expected output.

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B. Simulation

For the simulation, we numerically inject the first 3000 data points of the Santa Fe time-series optically into the delay-based RC using the different optical input configurations for training. We have chosen a balanced MZM, an unbalanced MZM, a balanced MZM combined with a PM and also only a PM for this. The injection of data into the reservoir is performed by a convolution of a preprocessing mask, consisting of 5 different piecewise constant sublevels, with the input data. This masked signal is subsequently multiplied with an amplitude, and possibly with a bias in the case of the (un)balanced MZM, and is defined as the modulator signal B. The NMSE is calculated on the testing set, which are 1000 data points of the Santa Fe time-series and which are different from the training set. The NMSE for the different input configurations are shown in Fig. 1 for the total range of the phase modulator signal B. Every numerical experiment is repeated 10 times for the average NMSE and standard deviation.

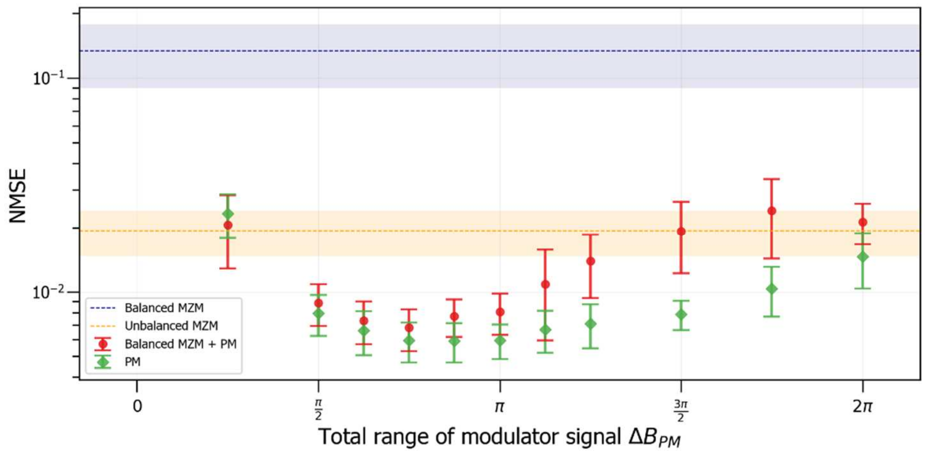

Figure 1: NMSE as a function of the total range ΔB_{PM} of the phase modulator signal for one-step ahead prediction of Santa Fe data.

Fig. 1 shows the NMSE when using the balanced and unbalanced MZM as input configuration, in blue and orange. It demonstrates that the unbalanced MZM outperforms the balanced MZM as input configuration, even with identical amplitude and bias values for both MZMs. This is most likely due to the fact that the unbalanced MZM modulates both phase and intensity of the injected field, whereas the balanced MZM only modulates the intensity of the injected field. This can also be confirmed from Fig. 1, where we show the NMSE of the balanced MZM combined with a PM, in red. If we combine the balanced MZM with a PM, of which the latter also modulates the phase, we observe improved performance compared to using only a balanced MZM, thus confirming the importance of phase modulation. From these results, one could ask whether a MZM is needed to inject the input data, which could ultimately reduce the complexity of the input configuration. In order to confirm this, we only use a PM to optically inject the input data. This is shown in green in Fig. 1. We observe that the combined input configuration of a balanced MZM and PM has similar NMSE values as using only the PM, both as a function of the amplitude of the phase modulator. Both input configurations initially decrease with an increasing total range of the modulator signal, then reach an optimal point and then again increase for larger total range of the modulator signal. The optimal point, and thus the lowest NMSE, occurs for a broad range, between $\pi/2$ and π, and can be explained due to two factors. For small total modulator signal ranges, we are limited by the inherent noise which can hamper the masked data, so that the noise is indistinguishable from the different sublevels of the mask. For large total modulator signal ranges, the modulated signal will wrap on itself. These two effects will worsen the performance, which explains the existence of the optimal value for the total range of the modulator signal.

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