Dual-mode Semiconductor Lasers in Reservoir Computing

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Reservoir computing is a neuromorphic computing technique, that has steadily improved its performance and has highly versatile implementations. One successful implementation is a semiconductor laser subjected to feedback, which is suitable for integrated photonic design. This implementation however, relies on long delay-lines, a drawback for on-chip design. We propose to employ dual-mode semiconductor lasers to obtain an extra degree of parallelism. We show that the setup with a dual-mode laser can be used to reduce the delay-line.

Introduction to reservoir computing

Reservoir computing (RC) is a relatively new neuromorphic computing technique, that closely resembles the functioning of artificial neural networks (ANN). ANNs typically consists of a large number of randomly interconnected artificial neurons (nodes) trained to perform a specific task. The ANN is trained by feeding the network with known examples and adjusting the parameters of each node accordingly, to achieve the expected result. By feeding large amount of examples to the network, it starts to learn how to solve the task at hand. Nowadays ANNs are mostly simulated on computers, sharing the same computation speed limits. Development of dedicated hardware is going slowly, because of the extensive network to be mimicked. Furthermore, the training of ANNs can be quite time and resource consuming. Reservoir computing offers an inventive way to circumvent both of these drawbacks.

In reservoir computing (RC) [1], the last layer of the ANN is split off to form an output layer. The remaining part of the network, also known as the reservoir, has a fixed structure as well as fixed nodal parameters, as shown in Figure 1. This greatly simplifies the training procedure, since the nodal parameters of this single layer can be adjusted by a least square regression.

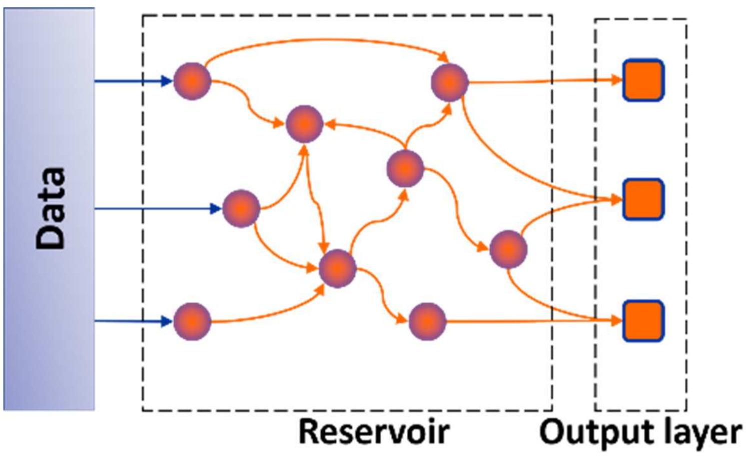

Figure 1 A schematic network architecture of a general RC scheme.

The computational power of ANNs arises from the complexity of the network, which maps the input data unto a very high dimensional state space. The same is achieved in RC with the randomly interconnected, but fixed reservoir. The fixed nature of the reservoir means that it can be replaced by any physical system with a complex dynamic response and an accessible high dimensional state space.
Over the years different dynamical systems have been proposed to serve as a reservoir. One particular RC scheme proposes to inject data into a single nonlinear node that is subjected to delayed feedback [2]. Delay systems are known to possess an infinite dimensional state space, which makes it well-suited for RC. The first electrical implementation of delay based RC was shown to have a good performance in 2011 [2], promptly followed by an optoelectronic delay based RC scheme, employing a semiconductor laser (SL) with electrical feedback [3]. A fully optical reservoir for a delay based RC scheme was proposed in [4], where an SL is connected to an optical fiber feedback loop. This scheme is further described in the next section. Van der Sande *et al.* [5] gives an extensive overview of current RC schemes and their (de)merits.

Delay based reservoir computing

In delay based RC scheme input data is injected into a single nonlinear node subjected to feedback. Suppose the task at hand can be represented by an input stream I(t), which is piecewise constant over an interval τ, where τ is the delay time imposed by the feedback loop . In order to increase the state diversity, the input data is multiplied with a mask M(t) which is periodic over τ and has N piecewise constant intervals of length θ within a period. The N intervals ensure that the nonlinear node remains in a transient regime and that each discrete interval level is mapped nonlinearly unto a different state. These states can be accessed by tapping into the feedback stream and sampling at every interval θ, also known as the nodeseparation. These sampled state values then form the virtual nodes, which can be linked to an output layer. A typical network architecture of delay based RC is shown in Figure 2.
An experimental setup employing a single-mode SL with a fiber loop was tested in [4], with delay times around 80ns. The setup proved to perform well for different tasks, including spoken digit recognition. This scheme lends itself very well for

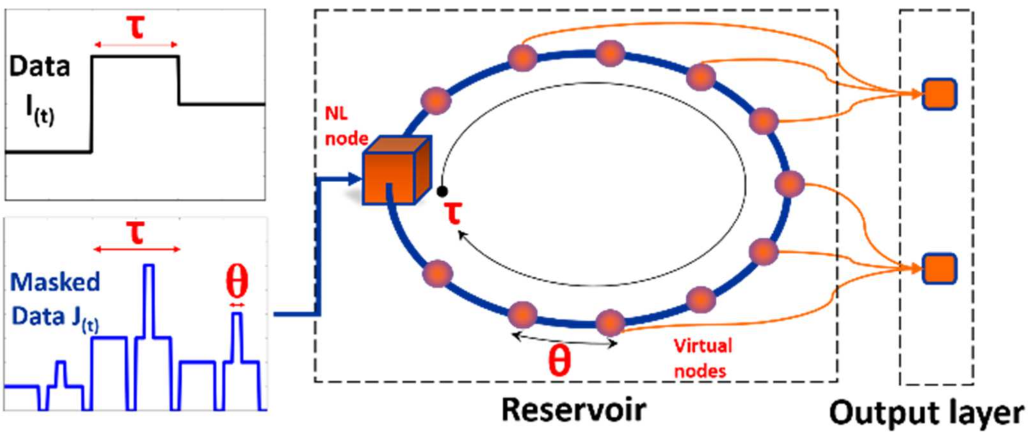

Figure 2 A schematic network architecture of a delay based RC scheme with a single nonlinear node, which in our case is a dual-mode semiconductor laser. .

implementation on an integrated photonic chip. However, the delay times need to be shortened drastically if on-chip implementation is to be achieved.

In order to shorten the delay time, we propose to employ a dual-mode SL instead of a single-mode SL. Having both modes propagate in the delay line, effectively doubles the number of virtual nodes. Hence, we expect similar performances for the dual-mode laser as with the single-mode laser, however at a shorter delay time.

Dual-mode delay based RC

The dual-mode SL model used in our simulations is developed by Lenstra and Yousefi [6]. This model considers the complex modal electric fields, as well as inversion moments, which corresponds to carrier gratings induced by spatial hole burning. The model can easily be extended to include more modes and moments, as well as terms to include optical injection and feedback.

The task used to benchmark the performance of our RC scheme is the laser generated timeseries from the Santa Fe timeseries competition [7]. The aim of this task is to do one-step-ahead timeseries prediction. The performance is measured using the normalized mean square error (NMSE), which can take up any positive value. A lower NMSE indicates a better performance.

As stated earlier, it is the dynamic behaviour of the reservoir which determines the performance of the RC scheme. Hence the reservoir parameters need to be optimized to obtain an optimal dynamic behaviour. In a dual-mode delay based RC the number of reservoir parameters roughly doubles, making linear parameter sweeps a tedious process. That is why a Bayesian optimization was employed to find the optimal set of parameters. Bayesian optimization forms a posterior distribution of functions that best describe the function we want to optimize, in this case the performance of our RC scheme as a function of the reservoir parameters. The more points in the parameter space are explored, the more the posterior distribution improves and regions worth exploring can be pinpointed with more certainty.

The Bayesian optimization is performed on three different schemes, a single-mode RC scheme and two dual-mode RC schemes. The difference between the two dual-mode schemes lies in the mask. One scheme has different masks on both modes, whereas the other has identical masks on both modes. The parameters included in the Bayesian optimization were the pumpcurrent, the intermode spacing, the modal injection and

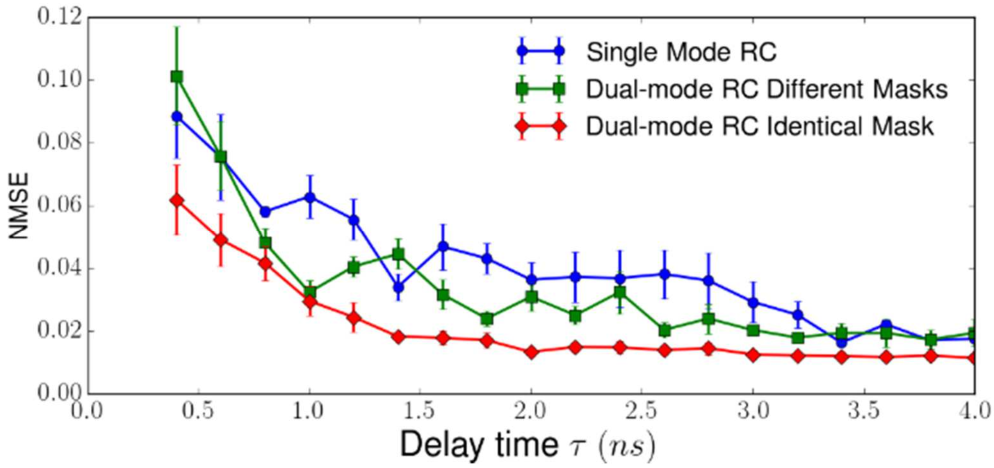

Figure 3 The performance of the three optimized schemes as a function of the delay time.

feedback rates. The nodeseparation θ was fixed at 20ps and the number of nodes N fixed at 200, leading to a delay time τ=4ns.
A linear sweep of the delay time is performed on the three optimized schemes obtained from the Bayesian optimization. Figure 3 illustrates the results of this sweep, showing the performance as a function of the delay time. The dual-mode RC scheme with identical masks clearly outperforms the other two schemes. The delay time can be reduced to 1.4ns before the performance gets worse compared to the best performance of the single mode RC. This result is counterintuitive, in the sense that one would expect the scheme with different masks to perform better, since the diversity of states would be higher in that scheme. However we think that the spatial hole burning is stronger in the case of identical masks, leading to stronger grating formations and consequently stronger modal interactions. This results in a more intricately connected network architecture that aids the computational power.

Conclusion

Employing a dual-mode semiconductor laser subjected to feedback as a reservoir, gives us several extra degrees of freedom to tune the dynamic behavior of a delay based reservoir. With the aid of Bayesian optimization on a partial set of reservoir parameters, we have shown that the delay time can be reduced from 4ns to 1.4ns.

Acknowledgements

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