

Photorefractive crystals as brain-inspired photonic reservoir computing systems

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Inspired by holographic data storage, we simulate small photorefractive crystals containing a random index variation placed in a cavity through which a pulsed bit sequence is sent. The light scatters and interferes with subsequent bits. By using the reservoir computing paradigm, the light leaking out of the cavity is interpreted by a linear readout neural network layer. Using this setup, simple bit recognition tasks are performed. In particular, XOR tasks between two bits with a separation of up to 5 bits, between two neighboring bits with a delay of 4 bits and header recognition up to a header length of 5 bits can be achieved with a bit error rate smaller than 10^{-3} .

Introduction

The photorefractive effect is a well-studied subject in optics. After its discovery in 1966 [1], one quickly realized that this light-induced charge transport in electro-optical crystals could be used in the context of holography and holographic data storage [2]. At the end of the century those photorefractive crystals were even used for creating all-optical neural networks [3]. Although the research in holographic data storage and other applications which rely on high optical bandwidth are still a hot topic today, those crystals were until now never used in the context of time dependent optical signal processing of time dependent signals.

In this paper, we propose a way to use these photorefractive crystals in the context of reservoir computing, a brain-inspired computing paradigm used for time dependent information processing. The idea of reservoir computing was independently proposed in the early 2000s by Jaeger [4] and Maass [5] as a way to train neural networks with internal feedback, with an as simple as possible training algorithm. This feedback creates a neural network where signals remain for a limited time: the neural network has a memory. Applying a time varying signal to some of the nodes in the reservoir ultimately results in nonlinear mixing of the signal. This complex signal is subsequently read out by a linear readout layer, trained on the dynamics of the reservoir, as is shown in Fig. 1.

One of the benefits of the reservoir computing approach, is that the reservoir itself can actually be used as a black box that transforms a low dimensional input data to a higher dimensional output space, in which classification of the signal becomes easier [6]. We use a photorefractive crystal as our dynamical system under the presumption that any system that exhibits those aforementioned properties can be used as a reservoir.

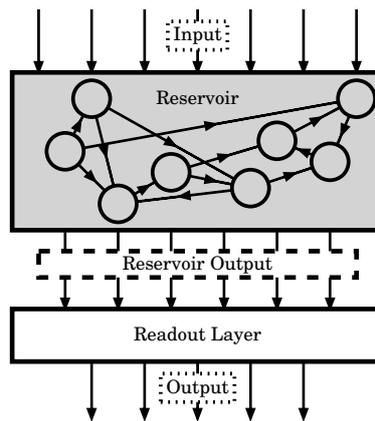


Figure 1: Typical reservoir operation scheme. A time dependent and possibly multi-dimensional input is fed into a complex neural network, for which the internal dynamics are unknown. The input signal mixes with itself in a nonlinear way, while the and the resulting reservoir state is read out at fixed time intervals. The reservoir state is in turn interpreted by a readout layer, which makes linear combinations of the reservoir nodes.

Simulation

The simulation of the photorefractive crystals is done using a self-written python module which couples the light propagation through the crystal with with the resulting excitation and transport of the charge carriers in the crystal. For this, Finite Difference Time Domain method got extended with the equations of Kukhtarev and Vinetskii (K-V model) [7]. The simulation generally consists out of two parts, a random hologram generation stage and a reservoir operation stage, as is shown in Fig. 2.

During the generation stage, a random index variation is written inside a small photorefractive crystal ($5\mu\text{m} \times 10\mu\text{m}$) until a maximal index variation of 5% around the mean

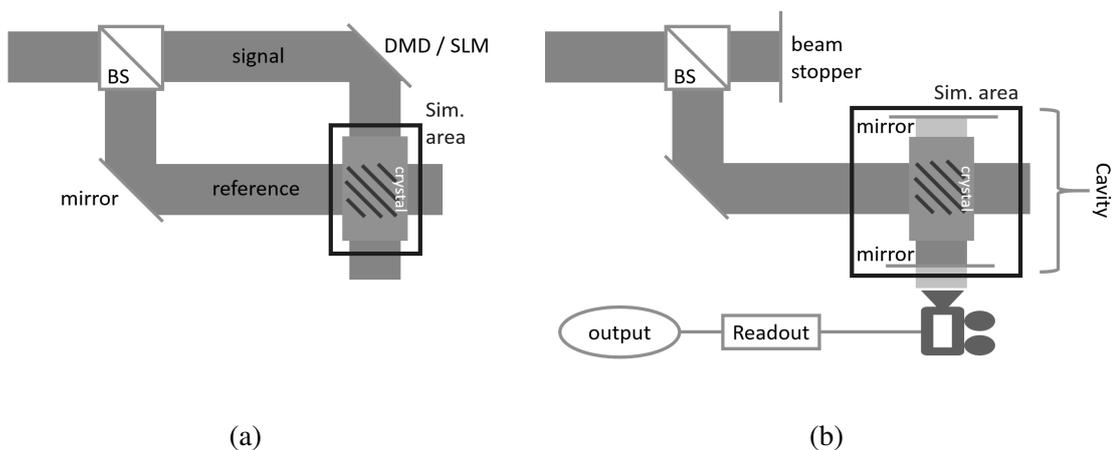


Figure 2: **(a)** Hologram generation stage. A random hologram is written inside the crystal and is kept fixed; **(b)** Reservoir operation phase. A random hologram is acting as a random scatterer. A cavity, consisting out of two mirrors, generates enough reservoir memory to perform simple bit tasks on the input stream.

($n = 2.2$) is reached.

During the reservoir operation stage, the crystal is put inside a cavity of two semi-transparent mirrors. Optical bits enter the cavity as light pulses for which the intensity is kept low such that they do not influence the internal index variation of the crystal. The light scatters through the crystal and interferes with itself, while the light leaking out of the cavity is recorded by a camera. As shown before [8], the readout process of a complex valued electromagnetic field ensures enough nonlinearity to perform simple processing on the time dependent input data.

During the simulation, the mirrors are put very close to the crystal, which ensures a round trip time of a bit pulse of $T = 2nL/c = 0.15$ ps. We match the bitrate of the bits to this roundtrip time. 10000 bits are then sent through the reservoir cavity while the readout data is stored. Half of the readout data is subsequently used to train different readout layers, each with a different binary processing task, such as XOR between subsequent bits and header recognition. The other half of the bits is then used to test the performance of the reservoir on these tasks.

Results

Delay As a measure for the ‘memory’ of the reservoir, a bit delay problem is proposed: the ability to reproduce an input bit with a certain number of bit lengths delay is measured.

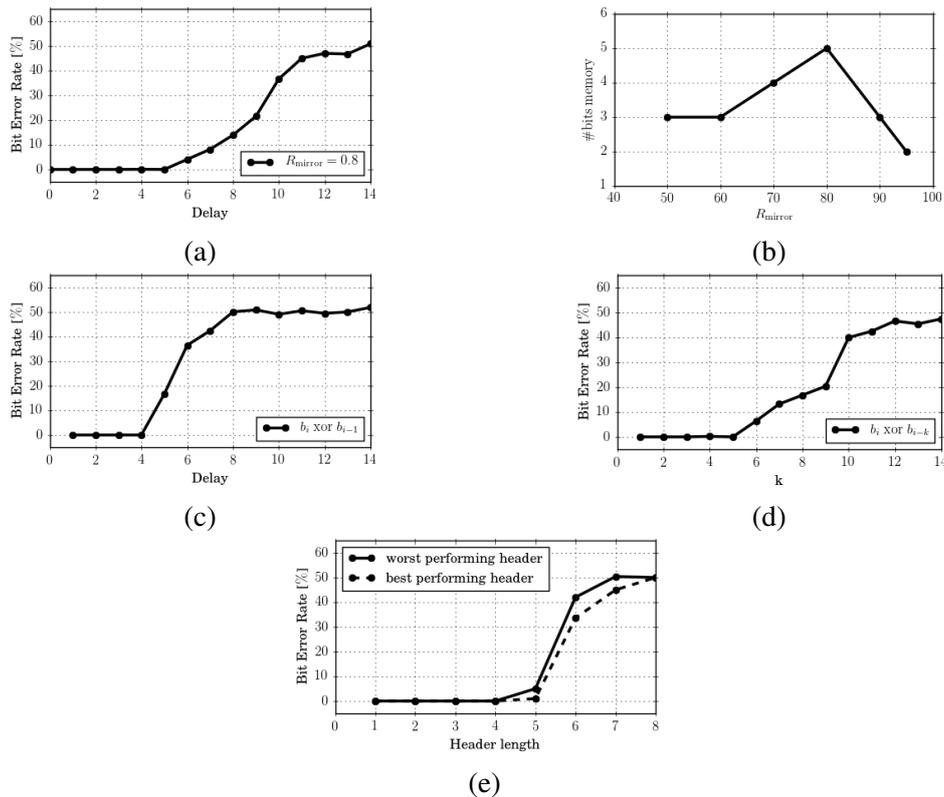


Figure 3: **(a)** Bit delay Error. **(b)** Maximal delay for which the input can be reproduced without error in function of the mirror reflectivity. **(c)** XOR of two neighboring bits with in function of the bit delay. **(d)** XOR of two bits with separation k . **(e)** Header recognition performance in function of the header length.

As can be seen in Fig. 3(a), a memory of up to 5 bits can be achieved. One would expect that the more reflective the mirrors are, the higher the memory of the reservoir will be, however, there seems to be an optimal reflectivity around 80%.

Boolean logic Because of the relative difficulty of performing the nonlinear XOR operation, the ability of performing an XOR counts as a good measure for the performance of the reservoir. Firstly, the performance of an XOR on two neighboring bits was assessed, while increasing the delay. This XOR-specific memory is a good measure of the duration the reservoir remembers the XOR results (Fig. 3(c)), although the performance is clearly worse than the delay memory, the XOR can still be reproduced up to a delay of 4 bits. Secondly, the XOR between two bits with variable distance k (Fig. 3(d)) was performed. We find errorless performance up to a distance of 5 bits.

Header recognition The reservoir also seems to perform reasonably well for header recognition tasks, with a minimal header length of 4 bits for the worst performing headers, while the best performing headers even reach 5 bits.

Conclusion

This proof-of-concept simulation shows that we can perform very high speed ($\sim GHz$) calculations with full size photorefractive crystals ($\sim 1cm$). Additionally, as the crystal size increases, the photorefractive effect will only increase, which will have a beneficial effect on the performance of the reservoir.

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