

Dynamics of coupled cavities for optical reservoir computing

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A reservoir network is a recurrent neural network with random connections. It maps some input signals or stimuli to a high-dimensional state. A weighted sum is made of all states, and those weights are then adjusted until they minimize a set of input-output signals (called the training set). Reservoir networks can solve tasks such as signal classification, signal prediction, ... One of the major challenges in the domain of optical reservoir computing is designing a network of optical nodes and designing appropriate readout methods. Theoretical study had revealed several candidate-optical components for these purposes.

Introduction

Reservoir computing is used to solve complex tasks such as speech recognition and deciphering hand-writing. They can also learn how to drive actuators to accomplish complex motions like moving a robot hand in a desired direction. Instead of programming complex algorithms, reservoir computing works in a way much more related to how the brain works. At this point, this has been successfully demonstrated in software, and our goal is to make a platform for reservoir computing using photonics technology [1]. This allows us to make very fast reservoirs with low power consumption.

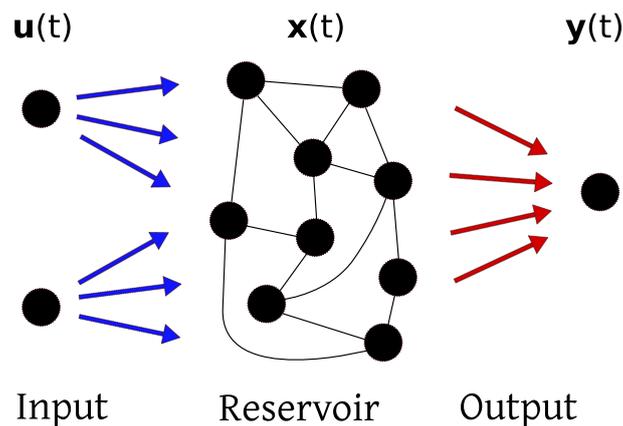


Figure 1: Layout of a reservoir network. Different time signals are shown: $\mathbf{u}(t)$ (input), $\mathbf{x}(t)$ (the reservoir states), and $\mathbf{y}(t)$ (outputs).

Figure 1 shows a typical reservoir. All arrows indicate a connection with a certain weight, all of them are random and fixed unless noted otherwise. For this reservoir, there are three types of connections:

1. From the input $\mathbf{u}(t)$ to the reservoir (blue). Examples of input data are: optical signals to be routed or regenerated, speech data, sensors from a moving robot, ...
2. Inside the reservoir (states $\mathbf{x}(t)$) between neurons (black). The reservoir is a highly nonlinear dynamical system. The topology can be sparse (low amount of connections) or dense (a lot of connections). Changing the weights of the connections can make the system stable or unstable. The reservoir performs best if it is on the edge of chaos.
3. From the reservoir to the output, $\mathbf{y}(t)$ (red). The weight of these arrows can be adjusted, which is called the `training` process. It is also possible to feed back information from the output into the reservoir, which is used for example in generation tasks.

In the modeling section, we briefly write down the equations describing the reservoir.

Basic Building Blocks

Using Silicon on Insulator (SOI) technology, we can create a multitude of components. Some of them, which can be used in reservoir computing, are listed in figure 2. Note that this list is far from complete.

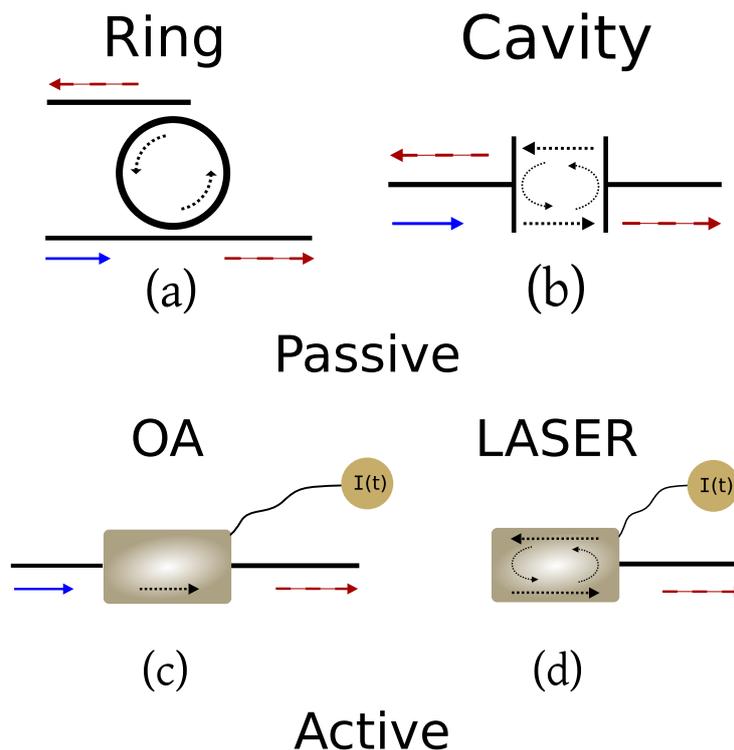


Figure 2: Basic building blocks for an optical reservoir network. OA = Optical amplifier. Blue (full) arrows indicate input, red (dashed) arrows indicate output, and dotted lines show the direction (a) or reflections (b) and (d) of the light inside the component.

They can be categorized in different classes:

- Passive or active. Although active components are easier to tune close to the chaotic regime, they are in general more difficult to fabricate because they need more processing steps. Here, we limit ourselves to passive components because they are easier to model and fabricate.
- Resonator type: standing wave or traveling wave. Standing wave-type resonators (mirror cavity, photonic crystal cavity, lasers) usually output power to both sides¹, the traveling wave outputs light along couplers in the direction in which the wave is propagating.

It has been shown in theory (see [1]) that semiconductor optical amplifiers in some cases perform better than software-based reservoirs. This is mostly because the equations that describe the SOAs are much more dynamic than the usual software reservoirs and they increase the state space dimensionality by adding a new parameter, namely the phase of the light.

The potential advantages of passive components lead us to investigating photonic crystal cavities and optical ring resonators. To enhance the nonlinearity, we can use a coating layer with a high nonlinearity, such as chalcogenides and polymers [3].

Modeling

To describe the reservoir we use the following equations in continuous time:

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{g}(\mathbf{u}(t), \mathbf{x}(t), t) \quad (1)$$

$$\mathbf{y}(t) = \mathbf{W}_{res,out} \mathbf{x}(t) \quad (2)$$

$\mathbf{x}(t)$ are the states of the reservoir, $\mathbf{u}(t)$ is the input, and $\mathbf{y}(t)$ is the output. The function $\mathbf{g}(\mathbf{u}(t), \mathbf{x}(t), t)$ can be quite complex and depends on the used models. It describes the dynamics of the optical reservoir, in which the states can be different variables, such as optical power, temperature, charge carrier density, ... To analyze the performance of the optical reservoir, we use a known dataset (the `training set`) of inputs and desired outputs. The inputs $\mathbf{u}(t)$ are fed into the network, and the reservoir states $\mathbf{x}(t)$ are calculated using equation (1). We then use the reservoir toolbox [4] to find the optimal weights $\mathbf{W}_{res,out}$, so that the output $\mathbf{y}(t)$ is close to the desired output. The reservoir is then tested using a new dataset (the `test set`). The reservoir performs well if the output is again close to the desired output.

Photonic crystal cavities are modeled using coupled mode theory. This theory has been validated through rigorous FDTD-simulations [2]. The phenomenological model includes parameters such as: resonance frequency of the cavities, phase difference between 2 cavities, characteristic power of a cavity, and detuning from the resonant frequency.

Simulation Results

Before we investigate big topologies, we make a rigorous analysis of some small topologies. This helps us in understanding and controlling the dynamics of the reservoir.

¹Lasers can be designed to output to both sides.

The used topology is a concatenation of three photonic crystal cavities. It seems that most of the parameters have a great influence on the dynamics. As an illustration, we change the input power P_{in} and observe the output power, see figure 3. Depending on the input power, one can distinguish regions of stability, self-pulsing and chaos. It becomes increasingly difficult to predict the regions of stability and instability if the number of cavities increases.

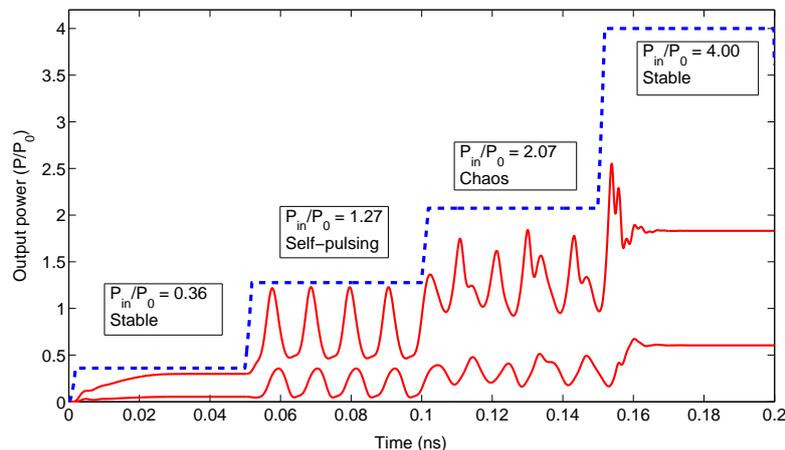


Figure 3: Optical power in some of the cavities. Different input powers show different regimes

Conclusion

Optical reservoir computing gives several huge advantages over software-simulated reservoir networks. They are very power efficient with respect to software reservoirs (measuring instead of simulating), and they are much faster. Using simplified models we can simulate the behaviour of passive optical networks and analyze them using a reservoir toolbox. This is the first step prior to creating the components.

Acknowledgments

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