A Photonic Implementation of Reservoir Computing

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Reservoir Computing [1] is a new approach to study and use Neural Networks, which try to mimic a brain-like intelligence. It uses memory and feedback in the reservoir to address more complex classification and recognition tasks as extracting time correlated features in problems like speech processing [2]. This has already been realized using software implementations but a hardware approach needs yet to be realized. Photonics offers a good platform to achieve this in a fast and economic way. The main idea is to build a photonic reservoir by exploiting and combining fast non linear light interactions to manipulate light.

Introduction

Neural Networks are networks that can be trained to solve complex classification and recognition problems. They mimic the nervous system in the brain, consisting of vertices which are interconnected end whereby every connection has a certain weight that can be adapted during the learning process. While feed forward neural networks (no feedback, figure 1) are well studied and understood, they are unapt for solving problems with time dependence. Recurrent Neural Networks are better suited because they have memory due to the feedback loops. The loops make the signal resonate inside the network for a longer time. Different problems and networks ask for different learning rules and it is very hard to make these rules general and to guarantee their convergence.

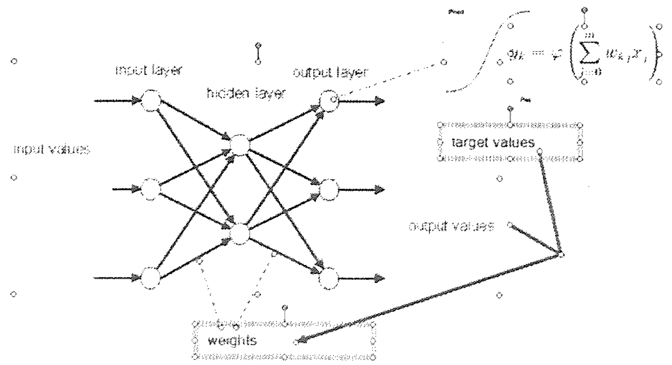

Figure 1: A feed forward Neural network with non linear function in the nodes

Recently a novel approach to these networks has been proposed: Reservoir Computing. The network is split up into two segments. The first one is the reservoir which is a RNN with random weights and which is further left untrained. The second one is the read-out function — it can also be multiple functions — which will be trained to solve a specific problem. The idea is that by splitting up the functionality the read-out function can be kept simple and therefore easy to train, while the whole system keeps its interesting computational properties - like extracting time dependent features - thanks to the reservoir. This can be seen in figure 2.
The reservoir transforms the input to a higher dimensional space where different classes cluster more and therefore they can be seperated easier by a simple plane (linear function) in this higher dimension.

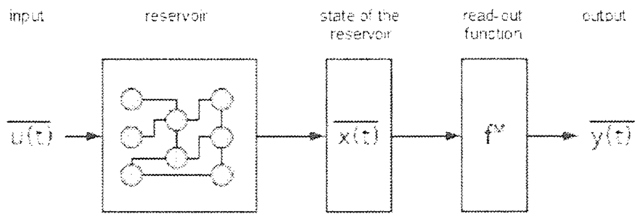

Figure 2: Reservoir computing

The implementation of Reservoirs has so far been restricted to software where they do as good or outperform present technologies.e.g. single word recongnition [2]. There is a need for a hardware implementation that performs in a power efficient way. Moreover the theory of Reservoir Computing doesn't limit the reservoirs to recurrent neural networks, because even a bucket of water can be a reservoir. Therefore a photonic implementation was proposed as a hardware implementation because it has properties which lead to a rich dynamical behaviour needed for reservoirs.
Photonics is the science which studies light and its interaction with materials. Nanophotonics tries to miniaturize the structures, needed to influence light, so that they would fit on a single chip. Given this it should be possible to develop a nanophotonic reservoir which is power efficient and very fast. It should be able to tacle all kinds of problems in an intelligent way, from the filtering of optical signals in telecom applications to speech recongition.

Implementation

The goal of this research is to develop a Reservoir based on nanophotonics. The reservoir will consist of different cavities which are interconnected. Inside the cavity non-linear effects will influence the properties of the resident light. These effects along with the degree of interconnection will determine the performance of the reservoir to solve complex problems. In a first stage the cavities will be studied until they are well understood. Different cavities will be evaluated like Photonic Crystal cavities (figure 3), Microdisklasers, SOA's,...

In the next stage they will be connected to form a reservoir. This reservoir will first be simulated and made into a hardware implemention to verify its computational potential.

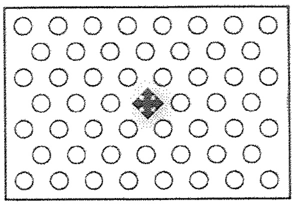

Figure 3: Photonic Crystal Cavity

Coupled SOA's

Semiconductor Optical Amplifiers amplify light linearly if the input power is small, but saturate for larger input powers. In this way they mimic the positive branch of a tanh function, which is used as the basis non linear function in analog Neural Networks (figure 1). This can be seen in figure 4[1] where a sketch of the steady state curve of a SOA is plotted. This photonic approach tries to stay as close as possible to the known Neural Networks concepts. We have written a simulator that can handle coupled SOA's and we will soon integrate it with the toolbox of Elis [2]. ¡¡ This toolbox written in Matlab can handle several neural network implementation as reservoirs. It can be used to verify the quality of a reservoir by testing it on different bench mark problems. Doing this it will be possible to verify the computational capabilities of a network of coupled SOA's.

There are some differences between the photonic approach and the software approach where one has to be aware of. Light is only positive so we have only positieve weights and the positive branch of the tanh function. First tests with the toolbox and analog neural networks indicate that this shouldn't constitute a fundamental problem.

On the other hand it isn't feasible to have a full mesh of interconnectivity between all the nodes as long as you work with planar photonic chips with only one level. This as well doesn't seem to pose fundamental limitations because small world networks seem to suffice according to the same simulations. Small world networks have a high density of local interconnections and only a few long distance interconnections.

Future work

In the near future the simulator for the SOA's will be integrated with the toolbox from Elis and if we would discover interesting reservoirs they will be fabricated.

[1] Picture taken from a presentation of J. Dambre

[2] http://snn.elis.ugent.be/

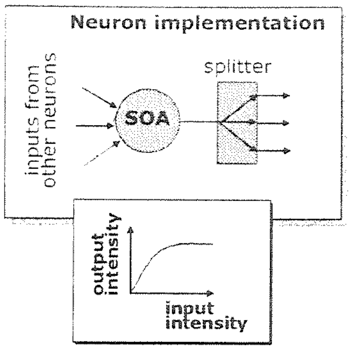

Figure 4: SOA as a neuron

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