Design of Oscillatory Neural Networks by Machine Learning Algorithms

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Introduction

Hardware accelerators for neuromorphic computing are in large demand. It is widely accepted that analog circuits could implement neural networks far more efficiently than the now omnipresent digital circuits, and they are better suited for analog sensory inputs. Despite this, analog circuits do not enjoy widespread adoption as it is difficult to implement robust, low-power analog circuitry in a deeply-scaled CMOS technology.

Oscillatory Neural Networks (ONNs) may be free from impediments of traditional analog circuitry [1], and they are also realizable by relatively straightforward nanoscale hardware. ONNs are however disadvantaged by the fact that only very few applications have been realized by them sos far, and these applications require fully connected networks, which are not easily scalable to larger numbers of oscillators.

In this work, we demonstrate how state-of-the-art ONNs can be designed by machine learning techniques, opening the way to new applications and simple, realizable network topologies. As an example, we demonstrate a Hopfield-network-like associative memory [2] that uses only nearest neighbor interconnections and that significantly outperforms Hopfield nets trained by Hebbian learning method.

Design of ONNs by BPTT

Backpropagation through time (BPTT) is a numerical technique to engineer the parameters of a dynamical system for a particular task. In order to use BPTT on an ONN circuit, we built a differential-equation-based compact model of ring oscillators (ROs), following [3]. This model is solved by torchdiffeq [4], in such a way that BPTT can run on the computational tree. This computing framework can automatically design the resistors which interconnect ROs so that the RO phases converge to a certain pattern. For a simple two RO case the procedure is illustrated in Fig 1. For many oscillators the BPTT can be used to engineer the couplings in such a way that classification on the MNIST database [5] is achieved. To test our method on MNIST each pixel of the input handwritten digits is applied as an input phase to nearest-neighbor connected oscillator network on a 14x14 grid.

The loss function can be defined so that the ONN acts as an associative memory – in that case phases representing the handwritten digits should converge to the image of an ideally-shaped digit. The resulting network is functionally equivalent a to a fully-interconnected Hopfield network trained by Hebbian learning, but performs this function using much fewer interconnections (see Fig. 2) and at a higher rate of correct classification.

Alternatively, the classification can be done by summing up oscillator outputs and recognize digits by the appearance of a high-amplitude output signal (see Fig. 3). For a single layer, the network achieves a 70% classification accuracy on the MNIST dataset, but an accuracy above 92% can be achieved by adding a very simple second classifier layer consisting of only 40 neurons.

In conclusion, we developed an 'in silico' training method for ONNs. The designed network can act as an energy efficient first layer of a neuromorphic processing pipeline.

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References

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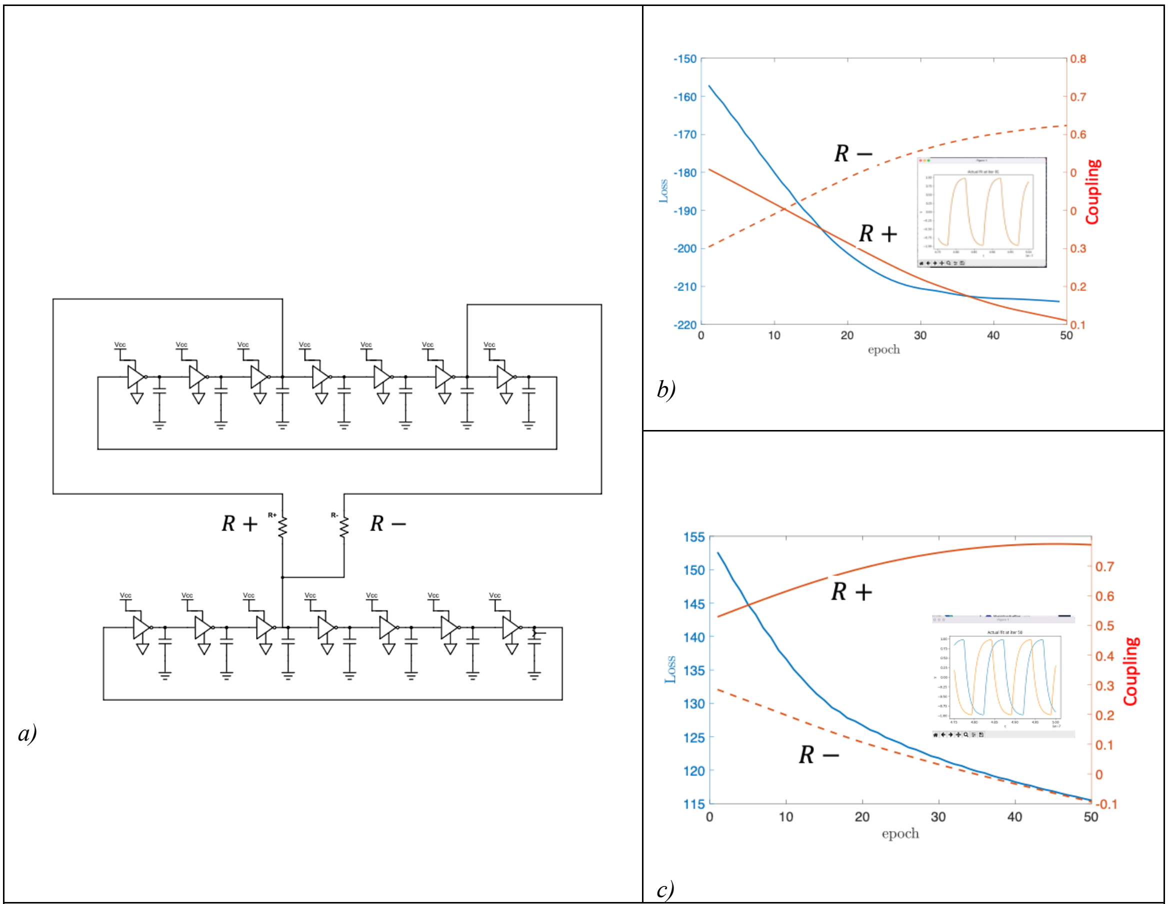

Fig 1. Machine learning the phase relations in a two-oscillator system. In order to couple the two Ros in phase, their like nodes should strongly couple, meaning that the R+ resistance should be small and R- large. For anti-phase coupling, R- should couple strongly, while R+ should be large. The machine learning algorithm adjusts the resistances until this state is reached, as shown in b) and c).

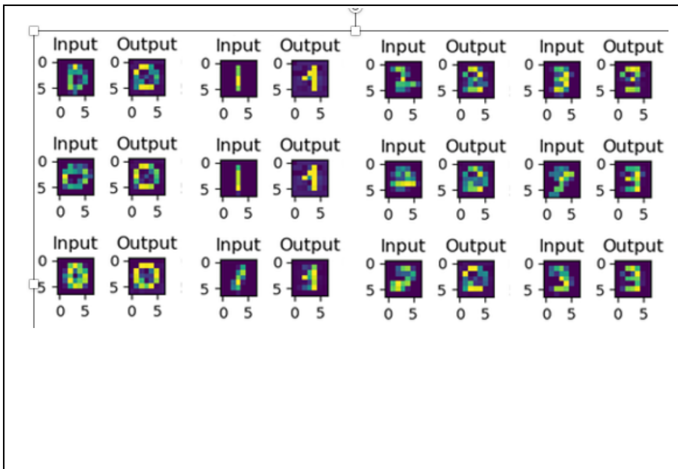

Fig 2. Associative function in a nearest-neighbor interconnected ONN. The images show the phase with respect to a reference oscillator. In most (but not all) cases the distorted digits (handwritten images) converge to the target digits.

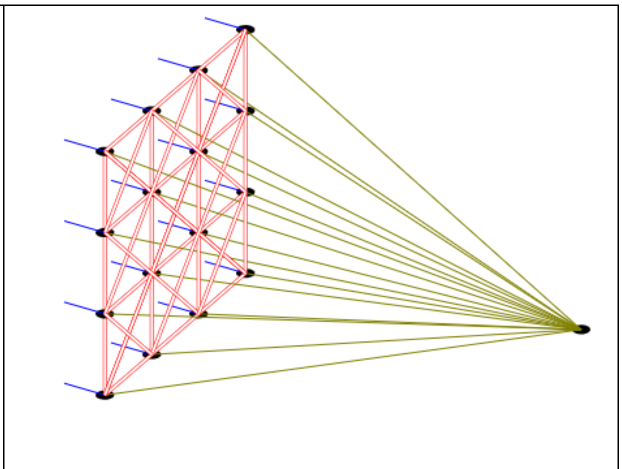

Fig 3. It is possible to get a single classification output by summing up all oscillator nodes. With appropriate learning parameters, this configuration leads to the highest accuracy.