Winner-Take-All Neuroorphic Architectures with Phase-Change Synapses

Severin Sidler – Prof. Yusuf Leblebici
LSM / IBM Research – Zurich
severin.sidler@epfl.ch

Introduction
The von Neumann bottleneck causes research to study alternative architectures. As such an alternative, neuromorphic architectures mimic our brain’s structure with a large number of small computing units (“neurons”) which are massively interconnected through “synapses”. These synapses are not only responsible for the communication, but also the memory. A compact way of implementing such neuromorphic architectures in hardware is to use dense crossbar arrays of memristive devices, every device storing a synaptic weight in its (analog) conductance state.

Theory
During a learning phase, the neurons should become sensitive to separate input patterns by adjusting the synaptic weights. A mechanism is needed to prevent the neurons to specialize to the same input patterns. One such mechanism can be Winner-Take-All (WTA). WTA reinforces the strongest output while suppressing all others. In spiking neural networks (SNNs) this is implemented through lateral inhibition. SNNs equipped with a Spike-Timing-Dependent Plasticity (STDP) learning rule and a WTA-mechanism are an approximation of Expectation-Maximization [1].

Motivation
This work studies the independent component extraction capabilities as well as the prototype learning abilities of a WTA-network. The network is implemented using phase-change synapses both in a hardware experiment on a phase-change array as well as in simulations using a matched model of the phase-change cells.

Independent Component Extraction
Independent component extraction is of use in multilayer artificial neural networks, where the first layer(s) typically extracts independent components. Furthermore independent component extraction ensures sparse coding of input patterns. We used the bars dataset [2] as input to a one layer SNN with all-to-all synaptic connections and 24 output neurons. The inputs are spike correlation encoded. The red neuron represents the WTA mechanism.

The network is capable of extracting all 16 independent components. The experimental final synaptic weights are represented below together with the sensitivity of the neurons during the training.

Prototype Learning
Prototype learning is important for clustering. The network should detect inherent similarities and group similar patterns together. As input, the MNSIT dataset of handwritten digits [3] is used. The images are encoded using a rate encoding and presented to a one layer SNN with 50 output neurons. The network was equipped with a homeostasis mechanism [4], a WTA mechanism and a simplified STDP learning rule [4].

The final weights of the ideal simulation are represented above and the accuracies are reported in the table below. The differential PCM configuration uses two devices in a similar way as [5].

<table>
<thead>
<tr>
<th>Network size 50 neurons</th>
<th>Accuracy [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training</td>
</tr>
<tr>
<td>Simulation Ideal</td>
<td>78.82</td>
</tr>
<tr>
<td>Simulation PCM</td>
<td>54.32</td>
</tr>
<tr>
<td>Simulation differential PCM</td>
<td>69.92</td>
</tr>
</tbody>
</table>

The results demonstrate the prototype learning ability of the WTA-network.

References