Master internship offer 2020
Simulation and design of analog backpropagation for machine learning

Subject orientation : Advanced research at the cutting edge of the technology ; possible extension for PhD thesis

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1 Context

Over the last decade, deep learning algorithms and networks [1] have had a revolutionary impact on the field of AI, achieving commercially interesting human-level or better performance on tasks such as image recognition, speech recognition, translation, image captioning, etc...

Almost all of the achievements in this area are based on Von Neumann computing architectures (where the processor and main memory are separated) and using digital processors. However, as transistor technology scaling reaches its physical limits, the computational throughput using current architectures will inevitably saturate [2]. Furthermore, the extensive processor-memory data movements have become the dominated energy consumption [3].

Moreover, nature and in particular the brain do not work exactly on these models and recent works are beginning to identify promising new structures, in particular based on analog computation [4, 5, 6]. Finally, one of the reasons for using analog electronics to realize neural network hardware is that several of the operations in neural networks can

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be realized by simple analog circuits, eg. sigmoids, adders, simple multipliers. It is also believed that the fault-tolerant nature of neural networks will compensate for the lack of accuracy in analog realizations [7].

2 Subject positioning and objective

One of the most used training algorithms for conventional neural networks is the back-propagation algorithm [7] and in the last few years almost all implementations of this algorithm have been done using, digital processors. However, in the early development

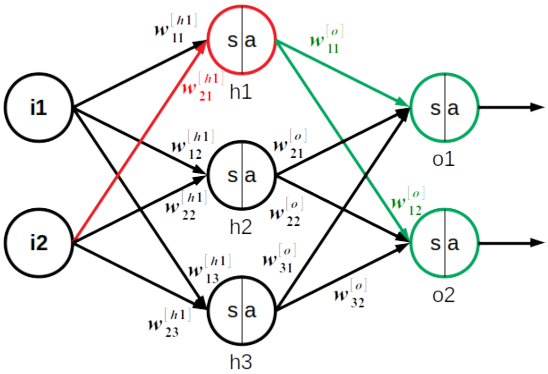

Figure 1: Diagram for computing the update rule of the backpropagation algorithm on the 2-3-2 multilayer perceptron

of the neural networks, several analog implementations of this learning structure can be found [8, 9, 10, 7, 11]

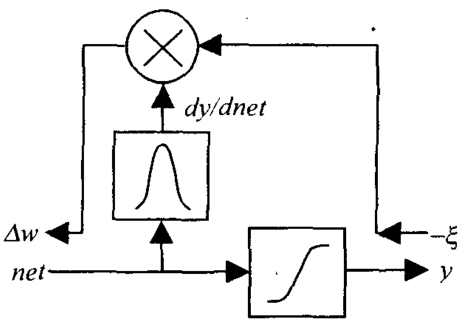

Fig. 1 Block diagram of BP neuron

Figure 2: Diagram from [11]

The aim of this internship is to demonstrate the interest of analog implementations using recent CMOS technology (such as 65nm or 28nm FDSOI) by simulating and designing an analog neural network with an analog backpropagation learning strategy.

3 Work Plan (6 months)

The research work plan is the following:

- State of the art of analog neural networks implementations and associated learning strategies (1 months)
- Matlab level simulation and electrical simulation of a complete ideal neural network (multilayer perceptron) (2 months)
- Matlab level simulation and electrical simulation of the analog back propagation system (on the multilayer perceptron) (2 months)
- Report & publication (1 month)

4 Required skills & tools to be used

- Skills in programming (Matlab/Octave)
- Skills in analog and digital circuit design

References

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