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Neural Hardware: beyond ones and zeros

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Abstract. An overview of research on the implementation of neural systems is presented in this paper. We focus on implementations where the algorithms and their physical support are tightly coupled. First, we concentrate on the potential of probabilistic algorithms to compensate for hardware non-idealities. Then, electronic circuits which aim to reproduce the structure of neurobiological systems in hardware are introduced. Finally, we extend to neuroengineering whose focus is placed on interfacing artificial devices with biological systems.

1 Introduction

Neural computing is now recognised as a useful paradigm in engineering. Complex non-linear problems that conventional methods fail to solve can often be addressed by artificial neural networks, almost always implemented in software. The platform on which the algorithm is to be run is normally not taken into account during the design stages. Clearly, the algorithms and the physical means by which they will be implemented in order to support the targeted application are not tightly coupled.

In contrast, some consider the physical nature of the computational elements required by their algorithms from the early stages of a design. Such work stems from the premise that neural algorithms in biological systems are significantly shaped by the potentials and limitations of the physical substrate on which they are implemented (wetware). Neural hardware researchers can also benefit from viewing the physical properties of materials inherent to electronics as opportunities to exploit in order to carry out neural-like computations.

This paper gives an overview of hardware implementations of neural systems as an introduction to the special session on “Hardware systems for neural devices” hosted at ESANN 2004. In section 2.1, some research in probabilistic computing in hardware is introduced. As technological advances create higher integration levels and demand lower power supplies, on-chip signals become more vulnerable to noise and other artifacts. Probabilistic computing has the potential to achieve useful information processing in noisy and corrupted environments. The paper continues with a short review of neuromorphic engineering - a discipline that mimics not only the high-level operation of neural systems, but also the low-level components that produce the characteristic behaviour of biological neurons. Following this discussion, hardware that

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interfaces directly with biological tissue will be presented. This area of research is commonly known as neuroengineering and will become important in the context of medical engineering. Finally, we briefly mention new research on the implementation of neural algorithms using implementation technologies which are still in early stages of development: molecular electronics, optical computing and quantum electronics.

2 Active Research

2.1 Probabilistic computing

Nanotechnologies and bioelectronics imply ever higher levels of integration and raise many questions regarding the physical integration platforms. The fundamental issues raised, however, go beyond simply integration to the need for intelligence, i.e. how to translate and use the knowledge and competence acquired by a system. Not only should it be 'intelligent', it must also be compliant with the technological issues raised by the drive to miniaturise and add functionality to integrated circuits (ICs). One immediate consequence of the on-going effort to fit more into ICs is that transistors sizes drop into deep sub-micron dimensions (i.e. below 100nm). This has the unfortunate effect of pushing CMOS process technologies closer to their limits of operation. The process parameters degrade with the decreasing device sizes, giving rise to lower supply voltage, larger leakage currents, larger coupling capacitance, worse mismatches... The signals of interest therefore become "infected" by many spurious factors, i.e. they become very noisy and less predictable.

Probabilistic computing offers a consistent statistical approach to deal with uncertainties and for extracting useful information from large data sets and thus has much to offer in the context of future silicon devices. Unfortunately most neural algorithms are poor candidates for hardware implementation [1]. For hardware amenability, an algorithm must be robust enough to cope with noise and imprecision. Stochastic Neural Networks such as the Boltzmann machine have proven their data modelling power. However most types of non-deterministic networks require extensive sampling to reach equilibrium. Their complexity is such that these settling times cannot be compensated for by hardware implementation and their direct translation into VLSI (Very Large Scale Integration) is far from straightforward. An unsupervised learning scheme with a simple and local learning rule would prove far more amenable to hardware. It would greatly ease the algorithm translation into a smaller number of more robust and reliable circuits.

One such algorithm, the Continuous Restricted Boltzmann Machine (CRBM), is presented in [2] and has been implemented in hardware [3]. It has proven to be able to detect abnormal heartbeats in [2] but also to compensate for sensor drifts in an ingestible capsule-sized Lab-on-a-Pill [4].

2.2 Neuromorphic Engineering

This discipline reaches beyond simply following the high-level operation of the neuronal systems found in biology to mimic the structure of the low-level components

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of these systems. Some neuromorphic work is based on idealised neurons which resemble their biological counterparts only because they generate spiking activity at the output as response to stimulations. Other neuromorphic investigations model, for example, very detailed phenomena such as calcium dependent effects in the sensitivity of the neuron to the strength of the input current [5].

In analogue VLSI (aVLSI), the laws of physics are very evident during the design process. Analogue VLSI designers build small integrated information processing devices using basic physical principles such as conservation and diffusion of charge. Hence, aVLSI is the most widely used implementation technology for neuromorphic engineering. Furthermore, well documented techniques to build integrated sensors in silicon (image sensors in particular) exist, which encourages the use of aVLSI in the neuromorphic context.

We will highlight three main goals in the design of neuromorphic systems. Firstly, many engineers are interested in building smart sensors. Animals have robust and optimised interaction with the environment implemented with limited ”hardware” resources. Thus, inspiration from neuronal system can help build better artificial sensors. This approach has been successful and now many imagers, silicon cochlea and other neuromorphic systems exist [6, 7]. A second group of researchers see neuromorphic systems as a tool to investigate neuronal models implemented in a physical substrate interacting in real time with the environment [8, 9, 10]. A final group sees neuromorphic systems as an opportunity to exploit some of the non-linearities of many physical devices. In general, however, many neuromorphic researchers are driven by a all of these goals, which are not mutually exclusive.

In [11], Carver Mead highlighted the fact that the movement of charges in the channel of MOS transistors operated in weak inversion is the result of essentially the same physics that determines the flow of charge across the membranes of neurons. However, this fact has proven difficult to exploit explicitly to build neuromorphic aVLSI circuits. Systems built over the last 15 years combine techniques from standard aVLSI design (current mirrors, differential pairs, push-pull inverters, etc) with basic building blocks developed by neuromorphic engineers. These include the current-mirror integrator [12] (a compact circuit widely used to introduce dynamics in silicon neurons), adaptive pixels such as that in [13] and Mead's axon-hillock circuit with a capacitive voltage divider [11].

As we have already mentioned, neuromorphic aVLSI has been used successfully to build complex sensory systems. Higher-level processing stages in a neuromorphic system should include adaptability, and therefore learning. Learning has been difficult to implement largely for technological reasons. Storing analogue weight values that result from many learning algorithms over long time periods is a task that requires large circuitry if standard design techniques are used. Technologies such as floating gates are often investigated for the storage of analogue weights [14, 15]. These techniques are, however, far from mature and reliable when used in the analogue domain. Recently, some investigations have focused on learning algorithms inspired by synaptic plasticity found in biological systems that produce binary weights (bimodal weight distributions) after analogue training [16, 17]. Such weights are far easier to store than are analogue values.

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2.3 Neuroengineering

The main goal of neuroengineering is to interface living tissue with artificial devices [18]. Clearly, important and wide-ranging biomedical applications exist, but neuroengineering also has an important role in neuroscience, i.e. in helping to correlate behaviour with neuronal activity.

Medical applications such as helping persons suffering motor disorders to communicate or control a prosthesis [19] inspire neuroengineers and demand a long-term, reliable interface between biological cells and artificial systems. Current systems such as the Brain-Computer Interface (BCI) use electro-encephalographic (EEG) activity to give some degree of control to the user [20, 21]. A working example is described in [22] where a BCI is used to control a web browser. Unfortunately this type of technology is not very portable. To gain portability and more autonomy these systems must be fully integrable and low-power. Furthermore, this type of recording does not allow for great accuracy. The signals are low in amplitude and measured across millions of neurons. They are merely an averaged representation of the global activity of a population of neurons and consequently lack resolution. This can be unacceptable for applications such as motor-control [23] where specific motor activity needs to be acquired and treated in real-time. The sensors must therefore be closer to the neurons of interest. This is normally done by surgically implanting small arrays of microprobes in the desired area of the brain/nerves. Since complex surgical procedures are needed to directly interface with living tissues or nerves, the devices implanted must have a significant life-time. The medical implants could possibly be cell-powered, i.e. fuelled by the metabolic energy of our body fluids [24]. However the power obtainable from biofuel is rather low [25] so the neural prostheses must be very low-power. MEMS (Micro-Electro-Mechanical Systems) technology is employed to fabricate the microelectrodes which come in contact with the neurons. Penetrating microwires [26] give the best results and have the longest longevity as the glial cells which feed and support the neurons grow well on them [27]. Despite the invasive nature of this type of probes, work in [28] has reported no discomfort or nuisance caused by such devices.
The applications for such types of hybrid systems are diverse and very exciting. For example, a recent breakthrough in brain interfacing described research in which 2 trained monkeys could control a robotic arm directly by their brain activity [29]. Microelectrode arrays were implanted in multiple cortical areas of these monkeys. Movements in primates are controlled by several interconnected cortical areas in the frontal and the parietal lobes. Accurate real-time and 3-dimensional movements of a mechanical arm were obtained from the processed neural activities recorded from the monkeys. Cochlea prostheses are another successful example of neuroengineering, with over 70 000 cochlear implants worldwide to date [30]. They allow the profoundly deaf to hear well enough to interact normally in our society and visual neuroprostheses for the blind are now also under serious investigation [31].

Studying specific details of the brain's computational power is not trivial, due to the limited access we have to the internal working of a live brain. MEA (Multi-Electrode Arrays) aim to give such access, albeit of limited scope. Entire networks of neurons can be cultured on electrically conductive plates. They allow multiple electrical signals to be monitored simultaneously. The electrode's circuitry is often

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bi-directional to also permit neurons to be excited. Work reported in [32] illustrates the use of MEA for studying in-vitro the learning capabilities of a neurally-controlled artificial animal; the Animat. Others [33] use hybrid networks of real and artificial neurons to permit the study of poorly understood mechanisms in the thalamus.

The type of electrodes previously mentioned only records electrical signals, while neural coding is both electrical and biochemical. It is therefore essential to fully understand neural plasticity/coding to also have an insight on the biochemical reactions of the neurotransmitters. Neurochemical sensors [34, 35] such as carbon electrodes electro-chemically transduce the neurotransmitter concentration into small currents (in the order of pA) [34]. Carbon nanotubes, a new product of microfabrication and nanotechnologies, also have the potential to be useful in this form of micro- and nano-interfacing. Their interesting chemical and electrical properties might be exploited as biosensors or nanoprobes [36].

The neural-electronic system must be capable of reproducing neural signals with high fidelity. A study of the physical parameters' effects on the measured action potential at the junction between the neurons and the probe is presented in [37]. Since transistors are employed to form the link to neurons, they should be exploited to include simple signal preprocessing (e.g. amplification, filtering...) within the neural interface. A typical neural interface comprises microelectrodes, preamplifiers, sample and hold circuitry, multiplexers, and amplified output stage. The new generation of neural interfaces also include wireless transmitters [26] to transfer the data to external peripherals. The preamplifier stage is of particular importance since it is the first stage to which the neural signals are fed. Biological signals are weak and must be amplified [38]. The added circuitry must have no other effect on the signals probed, such that the readings are immune from electrical interferences and artifacts placing stringent demands on the quality of the analogue circuit designs that are to be used for neural interfaces.

2.4 Alternative technologies

Alternative implementations of neural systems are being investigated. An example of such an alternative technology is optics. Optical neural networks [39] use optical signals (laser) with variable focuses for neural signalling and computation. Other work in [40] points towards new types of hybrid semiconductor/molecular (CMOL) devices suitable for nanotechnologies. The implication of such defect tolerant nanoelectronic neural networks could be very significant for future technologies. Finally, as devices become smaller, quantum effects will dominate the behaviour of computing elements and quantum neural computing may become a reality [41].

3 Conclusion

Motivations for implementing neural systems into hardware are diverse. Neuroengineering's goal is to create a direct interaction between artificial devices and biological systems. A major part of this research field is in the context of medical applications (neuroprostheses). The primary objective of neuromorphic engineering is to study and

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then translate working biological principles into electrical circuits. It aims to replicate the neurons machinery in hardware to build smart sensors or investigate interactions of neural models with real time stimulus. Probabilistic neural algorithms offer a means of computing that works with the grain of analogue hardware. They have the potential to retrieve useful information from corrupted data sets. They are therefore a plausible candidate for computing in noisy highly integrated environments.

The unifying aspect of these disciplines is that they all bear upon the physical properties of their support technologies. Interdisciplinary research linking these disciplines together will probably emerge in the future. For example, neuromorphic and neuroengineering can be brought together for designing prosthesis that connect real neurons to artificial neurons.

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