Levels of Abstraction and Implementation Issues in Neuromorphic Engineering

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Abstract - The sudden realization of need to modify the machines at architectural level to exhibit intelligence has led many investigations in Biological systems. "Humans" being most intelligent living things are the subject matter. Human Brain is one of the complex system which we are still unable to understand and mimic. In our pursuit of emulating human intelligence using complex hardware systems, many interdisciplinary domains have emerged. Neuromorphic engineering is a domain where electronic systems are designed based on Bio-inspired architectures. This paper provides a Brief review of The Journey of Human race towards imitating human intelligence in machines. Various Facts, Theories and Hypotheses in the domain of Neuromorphic Engineering are discussed. This work outlines the various approaches, architectures, devices and methodologies used in Electronic Implementation of Neuromorphic Systems. This paper will act as primer for any researcher willing to implement morphological circuits. Here we have discussed the progress of current trends in implementation of Cognition in Machine. The gap between software simulation and hardware emulation, FPGA and VLSI implementation is debated. To reach to a wider audience the limitations and open research issues pertaining to Hardware implementation of Bio-inspired architectures are discussed.

Index Terms— Computational cognitive Neuroscience, Emergent, Intelligence, Machine Learning, Memresistor, Neuromorphic Engineering.

I. INTRODUCTION

Every human being thinks in his own way, machines also think in a different way" [1] said by Alan Turing, one of the pioneer in the field of Machine Intelligence. He kindled the thought of thinking machines.

"In war, whichever side may call itself the victor, there are no winners, but all are losers" [2]. If we stand on the side of Engineering, especially Electrical engineering, it has gained a much from both the world wars. The motivation of intelligent machines took a huge momentum during the World War II and the first milestone was breaking Enigma, by Turing.

The need of intelligent devices is driving the current industry. Smart devices have made us very comfortable and reduced redundancy. We are in Pursuit of Intelligence now.

How to imitate human cognition? In pursuit of Intelligence we (scientific community) started to evolve our decision making algorithms, such as machine learning, pattern classification etc., [3-5], which accounts for Computational Intelligence. Another approach to mimic nervous system was neural Networks [6-8], which rather became mathematical computation without any idea of Hidden layer of psychological component. Swarm intelligence and Genetic algorithms were the recent achievements in computational intelligence. This segment of Bio-Inspired computing gave some promising accuracy in decisions but yet they were still algorithms that enabled machines to take more human like decisions. Cognition is not achieved yet[9]. By only developing complex algorithms and implementing in software, intelligence is not accomplishable.

There was a tremendous research in Hardware sector too, where sensors and actuators evolved a lot. They were miniaturized such that they can be embedded. These systems made machines to change or to take some predefined decision for any change in external environment. These systems were smart but not intelligent.

Software Technology is ever evolving, the pressure on hardware industry for incorporating more ICs in a single chip is increasing. Scaling in VLSI chips is finding its limitations due to secondary effects. Moreover the demand for intelligent machines is posing new challenges to chip manufacturers. The only way to mimic human intelligence in machines is to build the architectures of computing devices based on our nervous system [10]. Neuromorphic Engineering appreciates various concepts of biology and allows a designer to incorporate ICs based on bio-inspired architectures as in [11-15].

Section II brings out the various Hypotheses required to transit from existing computing architectures to Neuromorphic Architectures. This section defines Intelligence as an Emergent Phenomenon arising due to interactions between various cognitive processes. Section III outlines the facts and Flaws of Computer architectures and compares with human nervous system side by side. Information Transmission and signal processing in both the architectures are compared. Section IV describes the levels of Implementation of Morphed circuits, discussion of which is the important contribution of this review paper. Section V deals with Open research Issues and paper concludes with future work.

II. Hypotheses

All control and automation happens through a processor in digital domain. Till 1980s the IC industry was working with a motto of "Small is Beautiful" [16]. This miniaturization was accomplished by MOS Scaling. The next decade was of the motto "Speed is the Need". This high speed computing was accomplished by Dual, Quadra and Octa core which exhibited high speed parallel processing [17]. But these machines do not exhibit human behaviour. In last two decades we are striving to achieve machines which can imitate human intelligence. The main difference between machines and humans is cognition. This cognition is integration of all human behaviour such as attention, perception, learning, recognition, pattern classification etc…

Hypothesis 1: Machines built on high Parallel processing technology are not intelligent as they don't exhibit cognition.

Computers were designed assuming that man is programmed in childhood and executes or take decisions as the child grows. The architecture was designed on this concept of data accumulation, programming, storing, processing, and executing. There was no consideration for emotions, behaviour, beliefs, faiths, desires and intensions etc., which are fundamental aspects of cognition.

Cognitive behaviour is termed as Intelligence. To understand intelligence we need to know how Brain works. Human brain exhibits adaptation and Learning which is not found in machines.

Hypothesis 2: System/Machine is said to be intelligent if it exhibits Adaptation and Learning.

Learning is process of accumulating data, processing it, and extracting information from it. Learning also involves unlearning. Learning can happen at any moment, it's a continuous process. Once the knowledge is applied and experienced then patterns and entities arise there by intelligence emerges.

To tell a machine is intelligent, we don't have any touchstone experiment. From the beginning of computing every new feature which demonstrated autonomy was said to be intelligent. Later when machines were able to have computational excellence, controlling its environment, have communication between different or other computing devices were called as intelligent machines. When the features became common in every machine then those systems are called smart devices.

The very basic understanding of data collection, storage, processing, representation, Knowledge base, and execution in human brain will give us insights into human intelligence [18, 19]. The best way to understand a human brain is to simulate one. This might look impossible but we cannot deny that it is within our grasp.

Hypothesis 3: If we reduce the differences of Information representation, Transmission, storage and processing; between computers and humans then our machines can be more near to intelligent machines.

How to achieve intelligence in machines? According to hypothesis 2, a machine is said to be intelligent if it exhibits learning. To be more human like a machine should be able to learn in unsupervised conditions. Reinforcement algorithms are best suited [20-22]. Generally any algorithms which adapts to a new situation and takes the decision with a goal to achieve maximum rewards is Reinforcement learning algorithm.

The biggest limitation of Reinforcement learning is the "Curse of Dimensionality"[1] [23, 24]. The algorithm doesn't consider cognitive components and lack emotional entities. Cognitive models are very good for emotions but lack learning. It would be more near to human if we implement Reinforcement Learning Algorithms based on Cognitive models.

Hypothesis 4: Computational Cognitive Neuroscience based reinforcement learning will be more human like.

III. Facts and Theories

Confucius [25] once said, " I hear and I forget, I see and I remember, I do and I understand", to understand the complex functionality of brain, we need to build one. This goal has been driving many neuroscientists, engineers, psychologists who have come together in a single umbrella of Neuromorphic Engineering. Neuromorphic Engineering is an interdisciplinary domain which takes inspiration from neuroscience and tries to emulate the functionality, especially Brain. Miniaturized electronic devices built on the brain's architecture could answer many neural disorders. We can understand the brain malfunction and implant artificial vision systems, auditory systems as in [26-30] etc..., to restore vision, audibility and many other cognitive behaviour.

A. Some Facts

Though our computers are faster than individual neurons, still neurons outsmart computers when it comes to tasks such as pattern recognition and visual processing. The gap is because of the architecture on which our modern day computers are built.

The neurons communicate between themselves through spikes, which are membrane potentials and asynchronous. This is a characteristic of random analog signals, whereas such analog communication is not possible with synchronous digital systems.

Brain modelling can be approached in two ways: one way is start from modelling a neuron, observing the neuro dynamics, structure, and communication between neurons, later proceeding towards network of neurons. The outer way is to approach from one behaviour keeping in mind and implementing every minute details of biological systems into machines. The following part of the paper brings out a brief review of Morphological levels of implementations i.e. component/device level, circuit level, storage level, access level and lastly system level.

For any giver input, an output is generated by a system. If the outputs generated for same set of input are changing, then the system is adapting itself by using feedback mechanism. The adaptation is decided by learning. This is the important aspect which modern day computers need to exhibit to be intelligent (hypothesis 2).

Most of the research carried is on the basis of software simulation of biophysics, but not physical emulation of biological neural computation. There is a huge gap between simulation and emulation details.

B. Dissecting Brain and Computers

There are 2 best computing devices on earth: Brain and Computers. We know everything about one and little about another [10]. We are in a process to realize something whose functionality and working is not clear on something which we have built earlier. The good news is we are a bit successful so far, but the tragedy is the journey has just begun.

The biggest question in simulating a brain is to simulate which part of the brain? And to what degree of fidelity? When do we feel “Mission Accomplished”? Are we going to challenge the millions of year’s evolution with 50 years old computers?

If we take computer analogy of human brain, brain would be hardware, mind will be software, computations being the algorithms and memory would be stored data. A child perceives the data in childhood, develop database by the Thought and Feeling process, develop mental representations as data structures and is programmed to work accordingly in future. The thing which differentiates child brain and computer is, human brain is capable of choosing the best possible reward in a new, unfamiliar and strange environment without being trained. The basic level cognitive tasks of Perception, rational, learning and memory, information processing and retrieval are the areas to work for.

Brain has different parts which are specialized in different aspects, as faculty in a university. The occipital lobe processes visual information likewise temporal lobe processes auditory information. Therefore the first thing we have to keep in mind is Application Oriented design is preferred over general purpose. Second thing is we can achieve massive parallelism and do high speed computation, but the concern here is low power, high fan-out capacity. Therefore “speed is not the need”.

Super computers in [27] are 1000 times heavier, 10,000 times bulkier and consumes millions of watts as compared to a brain. The challenge is to make neuromorphic devices compatible, implantable and low power. One of the biophysics lesson from highly specialized structures, such as ears and eyes is that the initial computation done by them is in analog domain. Most of the processing such as filtering, spectrum analysis and signal compression is done before sending to brain. The inner ear uses just 14 microwatts and could run for 15 years [31]. The challenge is to meet this lowest power consumption.

Despite the fact that, brain doesn’t execute coded instructions, instead uses spikes for communication between synapses, collectively brain seems to be faster. A staggering amount of 10 quadrillion (10^{16}) synaptic activity per second. The challenge is to achieve such a high connectivity and high fan-out capability.

Human brain is fault tolerant, and is only vulnerable during accidents and aging. It is said that von Neumann architecture mimics left brain, and we are in pursuit of Right part of brain which is responsible for being fault tolerant, reconfigurable and event driven. Learning is exhibited by this part of the brain [32-35].

Implementing neural networks on VLSI was the inception for the debate between Analog and digital. The real world signal being analog, the ears and eyes are processing the incoming signal directly without the need of digital conversion.

A comparison table shows the brain’s equivalent counterpart of computers.

TABLE I. COMPARISON TABLE OF BRAIN AND COMPUTER

functionality	***Brain***	***Computer***
Perception	Sense organs	Sensors
Data	Spikes	Current
Basic component	Neuron	Transistor
Signal processing	Analogous/mixed	Digital
Transmission	Synaptic activity	Wires
Hardware	Brain	Processor
Software	Wetware/ Mind	Operating system
Memory	hippocampus	Gate capacitance
Storage	Monolithic	Modular
Logic	Fuzzy	Digital 0/1
Connectivity	High	Poorly connected
Fan-out	High	Very low
Speed	Individually slow Collectively fast	Individually fast collectively slow
Power consumption	Low	High
Reliabilty	Redundant	Fault-sensitive
Cognition	Exhibited	Yet to exhibit

Thousands of Analog cells can work in parallel, leading to high number of operations per second. Analog computation treats transistors as complicated, non-liner devices with many physical considerations, which comply with neuro dynamics. Whereas digital computing considers transistors only as a switch.

Analog systems are more efficient than digital if precision is traded-off. This can be explained by an analogy of a chocolate. Consider a chocolate broken into two equal pieces P1 and P2, take another chocolate two more equal pieces P3 and P4. If we try to join P1 and P3, which will be an original sized chocolate, if precision is not considered.

But keen observations suggest that neurons can be perceived as A/D Converters. As a neuron collects all incoming spikes and based on the threshold it decides whether a spike has to be transmitted (logic 1) or not (logic 0). Analog signals require more circuitry hence more power. Our goal is to achieve Low Power consumption. This is where Digital systems come into picture.

Digital systems are more power efficient, précised, flexible, and most importantly immune to noise. They are robust systems and doesn’t change with temperature, power supply fluctuations and to variations in transistor behaviour.

The question is should we go with analog systems or digital one. One may take inspiration from biology where initial low power analog processing at sensory organs is followed by digital transmission of information towards brain. Signal processing on VLSI systems is an emerging field, where much of the attention is given for Mixed Mode signaling.

IV. IMPLEMENTATION METHODOLOGY

Modelling is a reductionist approach. Models reduce complexity and provide simplified representation of real systems. All neuronal dynamics is not yet understood, hence creating an exact replica is not under our grasp. Abstraction is done at every level to make our life simple.

Brain being the most complex system, its implementation can be studied in a hierarchy. The interactions of different neuronal components give rise to behaviour. Since behaviour is a collective function of different neural components, its abstraction is placed above system level.

Protein/Genetic level describes the genes structure. It’s a neglected/not yet explored field in Neuromorphic Engineering.

At Membrane Level, electrical and ion exchange happens. Transistor is often abstracted as switch: ON or

OFF. But the V-I characteristics shows that current flowing is smooth and steep function of applied Voltage. Transistors work in subthreshold region where the V-I characteristics resemble the current voltage relationships in molecular structures on surface of brain cells. Hence membrane level abstractions and implementations are done at transistor level.

Intra-neuron communication happens through synapses. Synaptic plasticity is the reason for the emergent animal behaviors: adaptation and Learning. In recent years the learning process has dragged more attention. Selective attention is the main functionality of this abstraction level.

The synaptic plasticity can be implemented using CMOS circuits. Memristors are an alternative, which also has answers to memory modelling. Large scale memristive fabric is yet to be realized. Selective attention, Efficient learning and memory modelling is the biggest open research issue at synaptic level.

Perceptron's implementation in 1950's was the pioneering work, which was foundation for implementation of Artificial Neural Networks on hardware. Perceptron is computational model of Neuron. Hodgkin-Huxley and Morris-Lecar [14, 15] models are conductance based which has high biological precision but comes with huge cost. Another type (Type II) are spike based such as Integrate and fire model which describe temporal behaviour of spikes which are earliest and simplest models [16].

Spikes are used in nervous system for information transmission. Intra neuron Communication is important aspect at system level. Address event representation protocol proposed in 1991 to mimic information coding of brain. AER assigns a fixed address to every neuron, by using which neurons continuously update their central system about their excitation levels. This updated info is sent to upper/higher layers.

AER is a communication protocol for spiking neurons between different layers [17-24].This field has attracted a huge community of researchers who are engineering various protocols for inter and intra chip communication. AER scheme resembles to the Internet Protocol (IP) addressing in computer networking where information is routed to individual host corresponding to the IP address.

TABLE II. COMPARISON TABLE OF BRAIN AND COMPUTER

levels	**Neuromorphic Correspondence for Implementation Hierarchy**		
	Hierarchy	***Neuroscience***	***Electrical science***
7	Behavior Level	Mind	Architecture
6	System Level	Brain system	Macro Block
5	Circuit Level	Local Neuronal population	Block/Cell
4	Component Level	Single Neuron	Perceptron
3	Device Level	Synapses	CMOS/ Memristors
2	Membrrane Level	Channel Ions	Transistor
1	Protein/ Genetic	Genes	------

Selecting the appropriate level of abstraction is very important [26]. We have choice of Top-down approach, where we arrive to the neuron model keeping behaviour in our mind. Here we intend to reflect all biological components due to which it may be expensive, and the models become too complex. In Bottom-up approach we generalize one model of neuron and climb up to behavior level where most of the time the models fail to replicate the biological counterpart. This ambiguity whether to choose top down approach (complex biological implementation, Biology has the upper hand) or Bottom-up approach (abstract level implementations, existing engineering technology has the upper hand) leads us to the Valley of Death

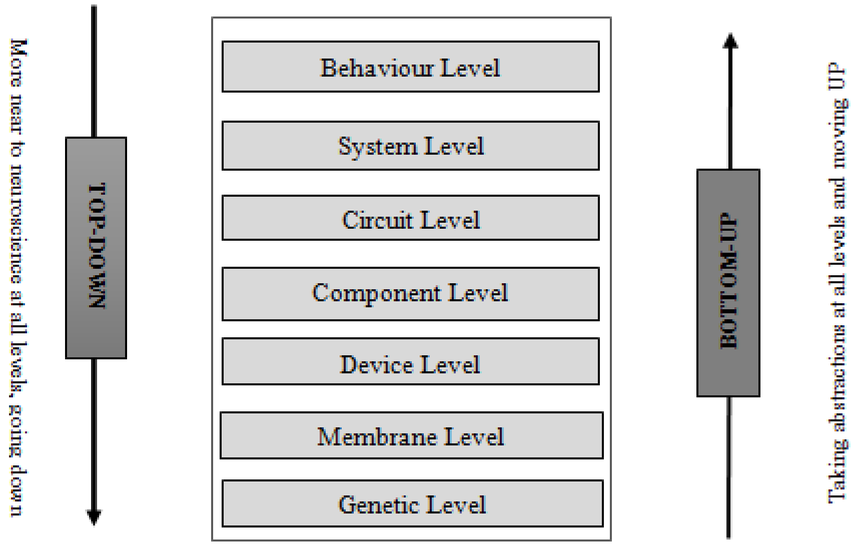

Fig. 1. Implementation Approaches

The 2 approaches are in fact 2 faces of same coin, no matter which approach we inculcate, the million dollar question is : "Is the machine Intelligent ?" finding the right trade off and compromises to make it more real (to humans) and realizable is the open research issue.

V. NEUROMORPHIC APPROACH

A. Brain cognition

The goal of Neuromorphic engineering is not only to mimic the architecture of biological nervous system but also to exploit properties of biological systems and mimic the human behaviour. By the existing systems we are unable to implement simple tasks performed by biological systems. Neuromorphic engineering applies computational cognitive Neuroscience principles discovered in living organisms to implement such tasks in Machines using CMOS VLSI Technology.

What's cognitive about Neuromorphic engineering? When do we say neuromorphic systems are cognitive? What are the different cognitive tasks of our interest? Neuromorphic engineering bridges the gap between existing engineering and Cognitive Neuroscience. Following are the humble attempts of it towards filling the gap including Neurolinguistics, vision and auditory systems, low power devices, locomotion, implantable chips(biomedical), which exhibit cognitive behaviour such as information processing, pattern classification, learning and memory, decision making etc…

B. Achievements of Neuromorphic Engineering

1) Vision system: This is the most explored cognitive tasks which has much interested audience not only from medicine but also robotics and automobile field. This huge vested interest is because they have immediate applications in sensors and sensory systems. The earliest vision systems was proposed by Mahowald and Mead [31]. Neuromorphic engineers have made significant efforts in copying the functionality of retina by designing analog silicon circuits which has led to wearable and implantable chips [26, 27, 32-35].
2) Auditory system: In 1997 researchers at Loughborough University designed a VHDL-based pitch detection system, and many implementations of bionic ears have been carried out in [30, 34, 36].
3) Microelectronic Nose: Mice and Bees demonstrate powerful and efficient odor discrimination capabilities. In [29], a microcontroller based electronic nose is explained. This is implemented using time domain encoding schemes to achieve gas identification. This pioneers translation of neurophysiological phenomena such as simple recognition, easy calibration, and training into hardware. The power consumption by sensor is of concern.
4) Brain: In [37] [38] the most ambitious project of "Human Brain Project" funded by European countries is aiming towards many aspects of Neuromorphic Engineering such as: Neuroinformatics, Brain simulation, High speed computing, medical informatics, neuromorphic computing and neurorobotics. SYNAPSE of DARPA [39, 40] aims to rebuild brain.

VI. IMPLEMENTATION ISSUES

The modern day simulations are slow, we not only have to implement behaviour also need to control them. Intelligent behaviour is about adaptation to any given circumstances with maximum rewards in long term. Humans are active receivers of information i.e. perception is not always data driven, it is Knowledge driven too A conclusion might elaborate on the importance of the work or suggest applications and extensions.

Hardware is more near to real time application but too tough for carrying research and implementing. Software has many assumptions and there is always a large difference between hardware and software simulation results. Here we compare Hardware and Software implementations, also FPGA and VLSI implementations.

It is possible to simulate these circuits in software. [41-45]. The high computational load can be taken care by parallel processing, but the real time environment needed for experimentation is not in the grasp of simulation.

FPGA has been popular in industry, education and research. The reasons for their overwhelming popularity is the flexibility for fast prototyping for implementation of digital designs without altering the hardware. Chip design demands large waiting period and puts a hole in our pocket. FPGA is continuously evolving and are available for a reasonable price. Xilinx is one of the manufacturer. Achronix semiconductors are providing new class of FPGAs with speed up to 1.5 GHz. The key change is the internal logic is asynchronous [46]. A direct transition from Simulink to FPGA circuit synthesis is possible as in [47]. To exploit the analog computation i.e. Simulink to Analog hardware conversion is possible, now the arrays are FPAA [48, 49].

More often Neuromorphic engineers rely on garden-variety VLSI, CMOS technology to experiment as in [50] there is much resemblance between VLSI hardware and neural wetware.

VII. CONCLUSION

In this paper we have given a critical review of different streams arising because of Cognitive sciences, Computational sciences, Neuroscience and Neuromorphic engineering. We brought out the Hypotheses, facts and Theories necessary to keep in mind while implementing brain models. There is a new field of science which combines psychology, Computer science, Mathematics, and Neuroscience and Electronic Hardware Design. The Cognitive Neuroscience computing is at verge to give rise for many potential mainstream applications. Neuromorphic Engineering is one such example.

It seems that we have taken a big leap, but much remains to be achieved. Any Engineer who want to jump into research of Brain Computer Interaction, Intelligent machines, Neuromorphic engineering has to know many trade-offs. This paper has done a brief review of various tradeoffs to be taken take during Hardware implementation of Bio-inspired Computing Architectures. Levels of Implementation is an important contribution of this paper. Implementation approaches provide a clear idea for a researcher to start at what level and what to expect from the upper layer and what services are necessary to the lower layer.

This paper brings out many open research issues pertaining to morphed circuits. Some milestones achieved are mentioned, and the things yet to be achieved are discussed. This has also discussed the gap between the software simulation results and Hardware emulation results.

Future work would be focusing on Learning and memory issues in implementation on Neuromorphic VLSI Chips. Reinforcement learning would be the focused field in Learning.

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