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Computational Models of the Brain

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Abstract: Different research projects around the world are trying to emulate the human brain. They employ diverse types of computational models: digital models, analog models and hybrid models. This communication includes a summary of some main projects, as well as future trends in this subject. It is focused on various works that look for advanced progress in Neuroscience and still others which seek new discoveries in Computer Science (neuromorphic hardware, machine learning techniques). In addition, given the proven importance of glial cells in information processing, the importance of considering astrocytes into the brain computational models is pointed out.

Keywords: brain emulation, neuromorphic chip, neuron-astrocyte computational models, brain computational models

1. Introduction

The first computational brain models were created with the goal of reproducing this extraordinary organ, in order to understand and mimic the way the information is processed, as well as its energy efficiency [1-9]. From these works, basically two scientific disciplines emerge: the connectionism branch of Artificial Intelligence, which is aimed at developing algorithms based on neural networks to process the information, and Computational Neuroscience which seeks to create realistic models of the brain. In the seventies the field of Brain Machine Interface (BMI) also emerged, whose purpose was to create systems that connected the brain directly to an external device. At the same time, a branch of

Neuroscience, known as Neuroprosthetics, was formed, which sought to build artificial devices to replace the functions of nervous systems which are damaged in patients. At the end of the eighties, Carver Mead [10, 11] proposed the concept of Neuromorphic Engineer to describe the use of Very Large Scale Integration (VLSI) systems which contained analog circuits to mimic the neurons.

All these scientific disciplines have tried to model the brain in one way or another. Over the past century, many experts in these fields have predicted that in 10 or 20 years a computational system comparable to the human brain would be built. But all these predictions had failed because of the technological limitations and the underestimation of the brain capacity. Although IBM ran the first simulation with approximately the same number of neurons as the human brain, the neuron models were very simple and the simulation was x1542 times slower than in real time [12]. However, it should be pointed out that until now in most computational brain models the capacity to process the information from the other half of the brain, containing 84 billion glial cells [13], has not been taken in consideration. According to the Neural Doctrine, neurons are the only cells in the nervous system involved in information processing, and the glial cells only play a support role. But over the past two decades this theory has started to be seriously debated. Some discoveries have demonstrated the capacity of the glial cells to participate in information processing [14-17]. In this communication, some works focused on implementing artificial astrocytes in the brain models are referenced.

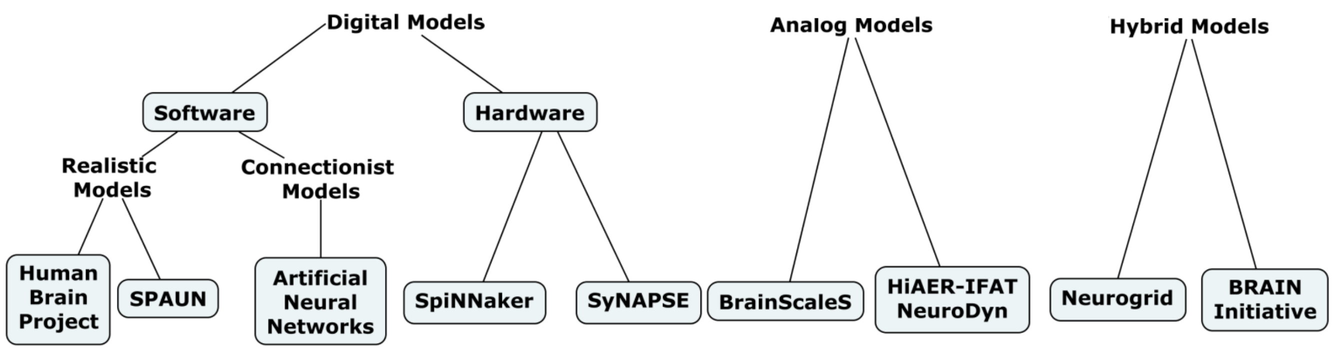

Figure 1. Brain Model classification.

2. Models Classification

Classifications of brain models can be performed from different perspectives. In this communication, different computer models that have been classified from the point of view of signal processing by hardware are currently under development, such as: digital models, analog models and hybrid models.

This classification is shown in Figure 1.

- Digital models: they compute information using the binary system to simulate and parallelize the behavior of the brain cells. From the software models, the realistic computer models are first considered, which are those shaping the internal structure of the cells (ion channels, organelles, etc.) allowing the study of their functions/operations. The generation of action potentials, activation of neurons, and synapse creation are simulated by mathematical equations implemented in the software, with specifically-designed tools. In addition, the connectionist models are taken into account, which, given a known behavior is expected to be achieved, such as a classification, object recognition in images, regression, etc., allow searching for a structure of artificial process elements (neurons and/or astrocytes) that give sufficient rise to such behavior. With regard to digital hardware models, they propose new computer architectures based on brain functioning.

- Analog models: they consist of neuromorphic hardware elements where information is processed with analog signals, that is, they do not operate with binary values, as information is processed with continuous values. This allows computation to be more efficient, so that analog computation could be used in applications where energy efficiency is very important.
- Hybrid models: they have been classified as such those assembled using hardware composed of both analog and digital components. These models seek to make the most of each type of computer.

Projects		Name	Institution	Num. neurons	Type of neurons	Simulated synapses	Objectives	Duration	Refs.
Digital Models	**Software**	Human Brain Project	European Union	10^6	Hogdking & Huxley	$5x10^8$	1, 2, 3, 4	2005	18
		SPAUN	Univ. Waterloo	$2.5x10^6$	Leaky integrate-and-fire	10^{12}	1	2012	19
	Hardware	SpiNNaker	Univ. Manchester	$2.5x10^5$	Point neuron models, leaky integrate-and-fire, Izhikevich's models	$8x10^7$	1, 2, 3, 4	2005	20
		SyNAPSE	IBM	10^{11}	Improved leaky integrate-and-fire.	10^{14}	2, 3	2008	21
Analog Models		BrainScales	European Union	$4x10^6$	Adaptive exponential integrate and fire neurons	10^9	1, 2, 3	2011-2015	22
		HiAER-IFAT	Univ. California at San Diego	250.000	Integrate-and-fire with two compartments for neuron	$5x10^6$	1, 2, 3, 4	2004	23-27
		NeuroDyn	Univ. California at	4	Hogdking & Huxley. 384	12	1	2004	23-27

		San Diego		parameters and 24 channels.				
Hybrid Models	Neurogrid	Stanford University	10^6	Quadratic integrate-and-fire somatic compartment + Dendritic compartment model with 4 Hogdking & Huxley channels	10^9	1, 3, 4	2007	28
	BRAIN Initiative	Qualcomm	not public	not public	not public	1, 2, 3	2013	29

Table 1. Overview of key features of relevant projects. Objectives (1. Computational Neuroscience; 2. Artificial Intelligence; 3. Neuromorphic chips; 4. Build devices to help disable people).

3. Characteristics of the models

Table 1 shows an overview of key features of main projects around the world that model the brain. In this table they are grouped according to the classification referred to:

Project name: it usually contains words like ‘neuron’, ‘spike’ or ‘brain’.

Institution: it is observed that most institutions are universities, but there are some projects developed in companies, such as IBM (SyNAPSE) or QUALCOMM (BRAIN Initiative). Most modeling works are coordinated by groups of the prestigious American universities, like Stanford (Neurogrid). There are also projects coordinated in prestigious European universities like University of Lausanne (HBP) or University of Manchester (SpiNNaker). The projects developed in European universities are mainly supported through the European Union, while in the case of US projects, funding comes from DARPA and NIH (National Institutes of Health). The most important difference between European and American projects is that Europeans try to increase scientific knowledge about the brain. However, the major American projects are rather focused on carrying out a revolution in the computer industry, laying the foundation for future computer systems.

Number of neurons: the simulation with the largest number of neurons was made by the SyNAPSE project in 2012 with 5.4×10^{11} neurons, a quantity even higher than a human brain, which is around 8.6×10^{10} [13]. It should be noted that this simulation is not expected to be realistic and uses very simplified neuronal models. Furthermore, the simulation runs 1542 times slower than real time and 1.5 million BlueGene/Q cores [30] were necessary.

Types of Neurons: there are many types of neuronal models with different levels of realism and complexity. These implementations can be either software or hardware-based. When it comes to software connectionist models, artificial neurons are simple processing elements which operate following sigmoid or threshold mathematical functions [31], although there are progressively more software models using built-in spiking neurons [32] that simulate action potentials. In the case of realistic models, the latter usually present ion channels responsible for the spike generation. The Hodgkin-Huxley model [9] requires more computational resources because it simulates Ca+2, K+ and Na+ currents. It is used in the HBP [18], Neurogrid [28] and NeuroDyn [26]. When the 3D arrangement of axons and dendrites is considered, the simulation becomes significantly more complicated, as a space-time integration is necessary. For the sake of simplicity, Rall's Cable Theory [33] and compartment models [34] are used. For more information about these models, please refer to [35]. The simplest model is "Integrate-and-fire point neuron", which adds the inputs to the associated weights and compares the sum to a threshold, resulting in a binary decision of either generating a spike output or not. There is an extension of this model that uses a charge decay, known as "leaky integrate and fire". It is used for example in SPAUN [19], SpiNNaker [20] and SyNAPSE [21]. Other ways to improve the models are: non-linear sum, time-dependent threshold, programmable delay in the release of the spikes and other variations.

Simulated synapses: in 2012 the SyNAPSE project achieves $1.37x10^{14}$ simulated synapses [12], roughly the same number as in the human brain. A problem encountered by the models is the synaptic connectivity because of the large number of existing connections in the brain. In addition, the connections between neurons are formed during development, but they change daily to allow learning. To date, the most common solution involves using networks with AER architecture [36, 37] that make neurons communicate only when they need to send a spike. The information is sent in a package that contains only the address of the neuron that fires the spike. The synaptic connectivity is stored in tables that are used by the network routers [38]. In analog models, the nearby connections between neurons are usually done through a direct cable. However, for long-distance connections AER is necessary, for which Analog/Digital and Digital/Analog converters are employed. This is a problem because the circuit that the neuron needs for conversion and routing is much larger than the neuron circuit itself. The brain modeling projects use supercomputer and CPU [39] or GPU clusters [40]. Moreover, others use neuromorphic chips specifically designed to process information emulating the brain, both digital (SpiNNaker [20], TrueNorth [21]) and analog (HICANN [22]), and even hybrid (Neurogrid [28], Zeroth [41]). One of the advantages of the neuromorphic systems is that, as they are implemented within the hardware, they eliminate the overhead of the simulation software, providing a more accurate output in a shorter space of time. Furthermore, the emulation speed and communication in neuromorphic solutions can be run faster than the biological equivalent. Another advantage of the neuromorphic solutions is that they have a lower consumption per emulated neuron. Although the analog model is faster, it has not been shown that its fixed neural structure adequately captures biological neural behavior.

Project duration: these are very complex modeling projects and works and, therefore, their time span is long. The case of Blue Brain Project should be pointed out, which began in 2005 and later became part of the Human Brain Project which is still underway. The older projects (started 10 or more years ago) include: Spinnaker, HiAER-IFAT or NeuroDyn. As seen in Table 1, the most recent is SPAUN. All of them are still under development, except for FACETS and BrainScales.

Objectives: most brain models are not completed, although some projects have already built parts of them that have been applied to certain fields or specific studies. On the one hand, the projects which are mainly focused on understanding some aspects of the brain were divided as follows: HBP is trying to simulate the effect of new drugs for brain diseases; SPAUN is testing neuroscientific hypotheses related to behavior studies; and the Neurogrid project is aimed at figuring out how cognition arises. On the other hand, there are models which allow automatic processing of large amounts of data using intelligent software (SyNAPSE, SpiNNaker). There are also projects that develop new processing hardware architectures, such as BrainScales, SpiNNaker, SyNAPSE. Finally, there are also some which allow even building devices to help disabled people, as in the case of the SpiNNaker project.

References: fundamental webs or papers, where the projects were presented.

4. Brain Computational Models with Glia

So far there were no projects including astrocytes in a neuromorphic chip. There are only realistic computational models [42-49] and connectionist ones [50-54] which have taken glial cells into account. Currently, there are two projects aimed at implementing astrocytes in neuromorphic chips, one is BioRC [55-57] developed by the University of Southern California and the other project is carried out by the University of Tehran and University of Kermanshah (Iran) [58-60]. Moreover, there is a project under development at the University of A Coruña, which extends classical ANN by incorporating recent findings and suppositions regarding the way information is processed via neural and astrocytic networks in the most evolved living organisms. Considering the works published over the past two decades on the multiple modes of interaction between neurons and glial cells [14-17], it would be a very interesting approach if most of these groups tried to implement these behaviors in computer models. In addition, it is worth noting that glial cells have evolved more than neurons. For example, in mammals there are no major differences between neurons of different species. However, a rodent's astrocytes may include between 20,000 and 120,000 synapses, while a human's may include up to 2 million synapses [61, 62]. Furthermore, the ratio between neurons and glial cells varies in different brain regions. In the cerebellum, for instance, there are almost 5 times more neurons than astrocytes. However, in the cortex, there are 4 times more glial cells than neurons [13]. All these data suggest that the more complex the task, performed by either an animal or a brain region, the greater number of glial cells is involved.

4. Conclusions

There are a great variety of projects and models of the brain around the world. The development of digital, analog and hybrid models is expedient and allows for advances in Neuroscience and Computer Science.

With regard to the cerebral phenomena emulated by computer models, the importance of considering the glial system should be stressed. Such system is crucial for the development of complex cognitive capacities of human beings. Therefore, it should be part of brain models to be truly realistic.

In the short and medium term, the modeling of the brain and neuromorphic chips will advance the development of prosthetic devices and Brain-Machine Interface. However, all the brain simulations that will be performed within this period will use very simplified models. It is therefore questionable that the whole brain could be analyzed through realistic simulations.

In the long term, it is more difficult to make predictions about the brain simulations, as their approach is rather philosophical than scientific. The question of creating an artificial brain is old, but today there is a clear division between scientists who believe it is possible, and could even be accomplished within the next two decades, and those who believe it will never be possible.

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Conflicts of Interest

The authors declare no conflict of interest.

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