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Parallel computing for brain simulation

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Abstract

Background: The human brain is the most complex system in the known universe, it is therefore one of the greatest mysteries. It provides human beings with extraordinary abilities. However, until now it has not been understood yet how and why most of these abilities are produced.

Aims: For decades, researchers have been trying to make computers reproduce these abilities, focusing on both understanding the nervous system and, on processing data in a more efficient way than before. Their aim is to make computers process information similarly to the brain. Important technological developments and vast multidisciplinary projects have allowed creating the first simulation with a number of neurons similar to that of a human brain.

Conclusion: This paper presents an up-to-date review about the main research projects that are trying to simulate and/or emulate the human brain. They employ different types of computational models using parallel computing: digital models, analog models and hybrid models. This review includes the current applications of these works, as well as future trends. 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). Their most outstanding characteristics are summarized and the latest advances and future plans are presented. In addition, this review points out the importance of considering not only neurons: Computational models of the brain should also include glial cells, given the proven importance of astrocytes in information processing.

Keywords: Parallel computation, Brain emulation, Neuromorphic chip, Brain computational models, Neuron-astrocyte networks.

1. INTRODUCTION

The human brain is made up of around 86 billion neurons [1] which communicate through synapses. Each neuron is connected to thousands of other neurons, giving rise to trillions of synapses. Each synapse can make around 200 operations per second, so the human brain could compute approximately 20 billion operations per second [2-6]. Some authors think that these values underestimate the brain capacity, and calculated around 10^{21} operations per second [7]. Moreover, some of the main characteristics of the brain are the fault and noise tolerance, concurrence, flexibility and high level of parallelization of the calculations. In spite of its huge calculation capacity and its amazing characteristics, the adult human brain only consumes around 400 Kcal per day, which represents nearly 25 Watts of energy output [8].

The first computational neural 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. In 1943, McCulloch and Pitts [9] proposed the threshold logic units (artificial neurons), which receive binary inputs with associated weights to the connection and they produce a binary output which depends on the threshold value. The interconnections of these artificial neurons form what is known as Artificial Neural Networks (ANN) or Connectionist Systems. Many neural models have been developed from this basic model. Some of the main initial contributions came from Turing [10], Minsky [11-13], Von Neumann [2, 14] Hebb [15], Rosenblatt [16], Hodgkin and Huxley [17], Widrow and Hoff [18], Hubel and Wiesel [19], Rall [20], Marr [21], Rumelhart and McClelland [22]. 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) emerged, whose purpose was to create systems that connected the brain directly toan 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 dam-aged in patients. At the end of the eighties, Carver Mead [23, 24] proposed the concept of Neuromorphic Engineer to de-scribe 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 in this review it will be observed that 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 [25].

However, it should be pointed out that until now in most computational brain models the capacity to process the in-formation from the other half of the brain, containing 84 billion glial cells [1], 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 [26-29]. A lot of studies suggest the existence of bidirectional communication between neurons and astrocytes, a type of glial cells of the central nervous system [30]. These evidences have led to the proposal of the concept of tripartite synapse [31], formed by three functional elements: presynaptic neuron, postsynaptic neuron and perisynaptic astrocyte (Fig. 1). The relation between these three elements is very complex and there are different pathways of communication: astrocytes can respond to different neurotransmitters (glutamate, GABA, acetylcholine, ATP or noradrenaline) [32] liberating an intracellular Ca^{+2} signal, that could be transmitted to other astrocytes. In addition, astrocytes may release gliotransmitters that activate presynaptic and postsynaptic neuronal receptors, leading to a regulation of the neural excitability, synaptic transmission and plasticity [33, 34]. The possibility of a quad-partite synapse, in which microglia are engaged [35], has recently been proposed. At the end of this review, further importance is placed on the computational models, besides neurons and synapses between the latter. Additionally, the works focused on implementing artificial astrocytes in the brain models are presented.

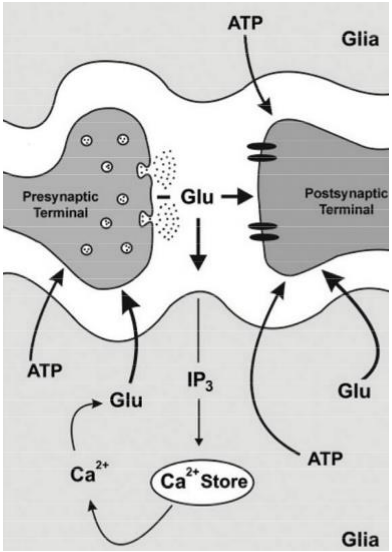

Fig. (1). Tripartite synapse.

In the next subsections, the motivations to create and develop brain models are listed. Then, it is explained how and why the classification of the projects was performed in this review. Finally, it is shown how information processing is parallelized in different brain models.

1.1. Motivations for Brain Modeling

Taking into account that the different scientific branches mentioned above have as a goal brain modeling, and according to Cattell and Parker [36], the reasons to build brain models are the following:

a) Computational Neuroscience: to understand how the brain works from a neurochemistry perspective, how cells and the different brain areas communicate or how synapses are created and modified, allowing the learning process to occur. Some of the projects focused on those aims are the Human Brain Project [37] or SPAUN [38].

b) Artificial Intelligence: to build new algorithms, inspired by the brain, to process the information better and develop systems with more intelligent behaviors. This is the case of the most recent models of ANN such as Deep Neural Networks. Over the past decade, a Machine Learning technique known as Deep Learning (DL) [39, 40] was developed, inspired by the high-level abstraction of the brain (Fig. 2). In recent years DL has shown the best results in pattern recognition, for example winning the ImageNet Large Scale Visual Recognition Competition [41]. Some of the applications of the DL techniques are: speech recognition and audio processing [42], object recognition and computer vision, signal processing, natu-ral language processing [43], information retrieval and multimodal [44] and multi-task learning [45, 46].

c) Neuromorphic Engineering: to build new hardware computer architectures based on the massive parallelism and adaptability of the brain. Nowadays the fastest supercomputer is the Tianhe-2 from China [47], with a performance of 33.86 Petaflops per second on the Lin-pack benchmark [48]. It has three million processors and consumes 17.8 MW. According to Moore's law, the number of transistors per unit area in integrated circuits is doubled every 18 months. This law has been fulfilled since it was proposed by Gordon Moore in 1965. At the present time, to simulate a human brain in real time using basic models, around 8.4GW would be necessary [49]. In accordance to Moore's law power-feasible brain-scale simulations would not be possible on conventional supercomputers unless the transistor dimensions sur-passed the atomic scale. But at this scale, around 1.2 nanometers, the phenomenon of quantum tunneling oc-curs. This effect allows a leakage of electron current that prevents the normal performance of the current transistors (MOSFET) [50]. Although Moore's law has its limits in the quantum scale, the Law of Accelerated Re-turns, proposed by Ray Kurzweil [51], stated that the exponential growth affects not only the number of transistors per chip, but the entire information technology and communications. There are different lines of research to design new processors: quantum processors [52-56], 3D processors, carbon nanotubes transistors, 3D graphene transistors [57-59]. This paper describes the neuromorphic chips that are based on the processing performed by brain cells, similarly to that carried out in the following projects: SyNAPSE [60], SpiNNaker [61], Neurogrid [62], BRAIN Initiative [63], BrainsScaleS [64]. There is also another line of research, aimed at developing brain inspired computing machines, the so-called Universal Memcomputing Machines [65].

d) BMI and Neuroprosthetics: to make devices which help people with different types of nervous system impairment; in this field, the hardest part is finding a proper way to connect the nervous system and the artificial de-vice; works that allow for progress in this respect are, for example, the implementation of MEAS *in vivo* [66] or the recent design of a simple artificial neuron that be-haves the same as a real one and could be applied to therapies for neurologic disorders: the critical role of transduction of chemical-electrical-chemical signal [67]. In this review we do not discuss projects with this motivation because aim to create only partial models with specific functions of the brain: BMI [68-70] and Neuro-prosthetics [71-74].

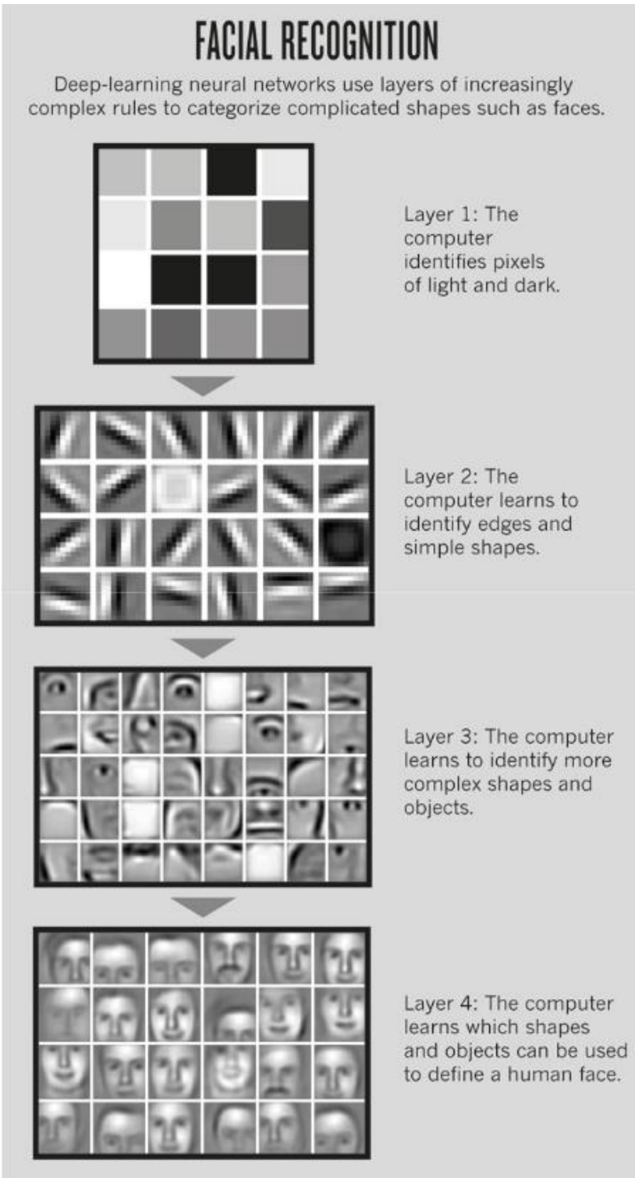

Fig. (2). Deep learning technique.

1.2. Projects Classification

Classifications can be performed from different perspectives using the works and projects that seek to model the human brain. In this paper, an updated review of relevant works is presented, with the aim of replicating the behavior of the brain, using parallel computing. Different computer models that have been classified by us 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 Fig. (3). Each type of model has some of the above-mentioned reasons or even several of them.

- Digital models: they compute information using the bi-nary 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. Examples of such tools which develop realistic models are NEURON [75], Genesis [76], Nest [77], etc. 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 are mainly explained by the above-mentioned point "c", as 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.

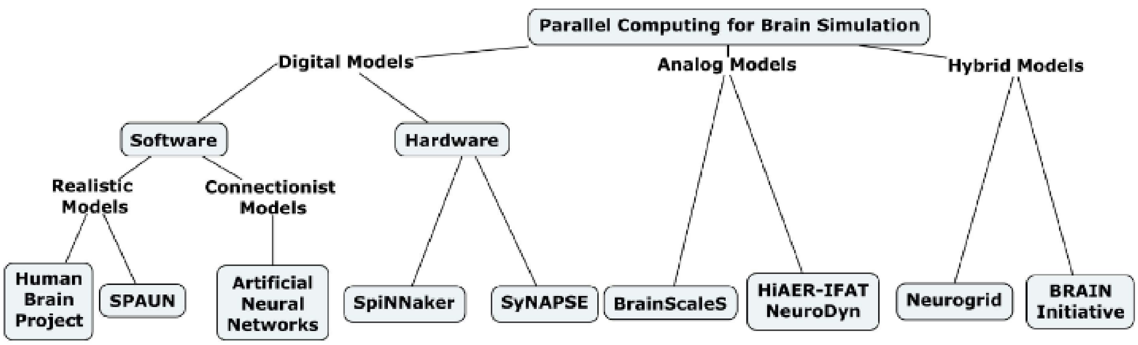

Fig. (3). Projects classification.

1.3. Paralellization

This classification has also been conducted because it allows understanding the need for parallelization and the as-sorted ways to parallelize the information processing from the modeled cells:

- Software Simulations with parallel processing: the models are implemented with software specifically designed for simulations. Their tasks are parallelized to run on different processing elements (central processing units -CPU, graphical processing units -GPU). Parallel calculations, necessary to simulate, for example, synaptic communication between cortical microcolumns of thousands of pyramidal neurons, are performed with CPUs of the Blue Gene supercomputer within the Human Brain Project (previously within the Blue Brain Project) [78]. An-other example is parallel training of an ANN with DL for pattern recognition using a cluster of GPUs [79]. These simulations are useful to study the quantitative behavior of neural networks. But they are not efficient enough to implement systems which behave appropriately in real time or large simulations of neural systems. Customized digital systems which make use of the GPU parallelism or the field programmable gate arrays (FPGAs) can act in real time, but they still lack the density, energy efficiency and resilience of neurons and synapses [80].

- Parallel Hardware (Neuromorphic architectures): the term 'neuromorphic' refers to hardware systems whose architecture and/or design principles are based on the nervous system [23, 24]. They usually comprise a large number of parallel arrays of simple processing elements in which the memory and computation are colocalized. In these architectures, the information is not processed with a clock frequency of the order of GHz, but rather the in-formation processing is spike event-driven. It means that the artificial neuron only computes when it receives an input. Thus, these systems reduce energy consumption by several orders of magnitude compared to systems employing the clock frequency [81]. Within this technique of parallelization, digital chips, analog chips and hybrid digital-analog chips can be distinguished:

    - Digital Chips: the neuromorphic chips that employ digital signals can be connected to each other and programmed to perform many tasks in parallel, for example, application-specific integrated circuits (ASICs) like SpiNNaker or SyNAPSE, which subsequently will be discussed in detail. Other examples of digital chips, which will also be mentioned briefly, are the special-purpose digital hardware, built with FPGAs [82, 83] and the recently proposed BRIC project which is aimed at using 3D technology to build a very efficient supercomputer [84].

    - Analog chips: they are neuromorphic chips in parallel, where the internal signal processing in the emulated neuron is analog. Such chips are based on the works carried out by Misha Mahowald [85-88] and Carver Mead [23, 24], and are based on the theory that the brain computes the information in an analog manner. The main drawbacks of analog computation are that it is inaccurate and sensitive to environment and manufacturing variations [36]. Within the analog chips a physical computation takes place, that is, it is computed by simply obeying the laws of physics. This should be considered in contrast to digital systems, which run a pre-given algorithm within a formal sys-tem, created to solve equations that are meant to de-scribe the behavior of a system. Put differently, in analog computers there is no separation between hardware and software, because the hardware configuration of a computer is in charge of performing all the computation and can modify itself [89]. Besides, these chips al-low investigating the strict real-time interaction of the system with its environment [90-94] [80].

    - Hybrid digital-analog chips. Parallel models are used by interconnecting neuromorphic chips with analog and digital components. Neuromorphic circuits that process information in an analog mode and perform communication in a digital mode are commonly used. In this way, neurons are represented by analog circuits and connections are made with digital communications, usually Address Event Representation (AER), a communication protocol proposed by Sivilotti in 1991 [95, 96]. The Neurogrid project and the Qualcomm Zeroth Platform from the BRAIN Initiative [97] should be mentioned as examples in this sense, detailed further on.

Therefore, this classification is considered globally for the development of this review, as well as the research projects to be addressed. In each specific section of the paper, the main projects/models of each type are described. Since there are already numerous publications and some reviews that describe the characteristics and objectives of many projects focused on brain modeling, the entire development of each work is beyond the scope of this study. To summarize them, an outline of the key features of each job/project to be treated is shown in subsection 2.2. In this table, along with the most relevant aspects taken into consideration with regard to computational modeling, the most recent leading studies outlining these projects are listed. Thus, this article is focused on the recent developments of each brain model analyzed.

The structure of this paper is as follows: Section 1 is the present introduction. Section 2 describes the context and state of the art of the reviews and articles on computational modeling of the brain. Section 3 is devoted to present the progress of the works and projects that carried out digital models of the brain. Section 4 points out the progress made with analog models and their differences with digital models. Section 5 presents the projects that use hybrid models of the brain. Section 6 covers the approach to the introduction of the glial cells in the computational models of the brain. Finally, some concluding remarks and a few predictions are made about what could be achieved in this field in the future.

2. STATE OF THE ART

2.1. Other Surveys

Currently, there are several interesting reviews published on brain modeling. The reviews analyzed were classified by us as shown in Table 1:

- Those focused on opinion and criticism of the models;
- Those describing and listing research projects which are carried out to model the brain;
- Those focused on analyzing existing models and theories about the brain;
- Those describing and analyzing analog neuromorphic systems;
- Interesting books with different opinions about the feasibility of brain simulation.

Table 1. Other surveys about brain modeling.

State of the Art	References
Opinion & criticism	[98-100]
Projects	[36, 101-105]
Model & Theories	[106-112]
Analog Chips	[80, 81, 113-116]
Books	[2, 89, 117-123]

2.1.1. Opinion & Criticism

In the review conducted by Eliasmith [98], technology, theoretical and empirical developments relating to the construction of sophisticated cognitive machines were analyzed. It also proposed and argued a timeline of progress in this field over the next 50 years. Based on these predictions, a system which simulates the entire human brain with 1011 neurons will be created by 2040. Finally, some of the ethical and philosophical problems that arose while developing this technology were analyzed.

Eliasmith and Trujillo [99] proposed two guidelines for large-scale models of the brain: first, consisting of a union of the models with the behavior, and second, the need to create models that can vary the level of detail of the simulation. Moreover, they made a list of the pros and cons of bottom-up and top-down models. They criticized bottom-up models which expected intelligent behavior to ‘emerge’ from models which were large enough.

The review performed by Matteo Colombo [100] argued that certain large-scale simulations of the brain were unable to obtain new knowledge about the brain. The author stated that new information could be obtained only about the computing performance and operation of the system itself.

2.1.2. Projects

In the review written by Cattell and Parker [36] the motivations and challenges of brain simulation are presented. It summarizes the main projects and compares them in terms of neural models, synaptic connections, learning and scalability.

Boris Tomas [101] presented a brief summary of brain simulation projects and raised some interesting questions such as: 'Is it possible to create a form of swarm intelligence artificially using network of simple nodes?'

Researchers from the Politecnico di Torino [102] wrote a review of the HBP neuromorphic computing project. They explained the difference between emulation and simulation strategies. In addition, this review summarizes the current status and objectives of the two Neuromorphic Computing Systems: Neuromorphic Physical Model (NM-PM) (FACETS- BrainScales) and Neuromorphic Multicore (NM-MC) (SpiNNakers).

Xiamen University researchers published a review in two parts. The first one [103] showed an analysis of the most important projects of brain simulation. Moreover, they presented a comparison of the simulation concept employed in each one. In the second part [104] they presented a summary of the BICA (Biologically Inspired Cognitive Architectures) classifying them into four categories: primarily symbolic architectures (e.g. ACT-R); emergent architectures (e.g. DeSTIN); developmental robotics architectures (e.g. IMCLEVER); and their central focus, hybrid architectures (e.g. LIDA, CLARION, 4D/RCS, DUAL, MicroPsi and Open- Cog).

Finally, Sandberg and Bostrom [105] carried out an extensive analysis of the concept of "Whole Brain Emulation" and the problems that could arise. In addition, a roadmap was included to this end, explaining the neuroscientific basis in depth. Different neural models, computational requirements and brain imaging technologies were summarized.

2.1.3. Models & Theories

A comprehensive review of the different neural models was written by Izhikevich [106], who compared the computational cost of the models and their ability to handle 20 characteristic behaviors observed in neurons *in vivo*. The computational cost is measured in number of floating point operations necessary (FLOPS). Izhikevich concluded that if the aim of the study was to find out how the physiological parameters influenced the behavior of neurons, the best model would be Hodgkin-Huxley [17]. But if the goal was to simulate a large number of neurons maintaining the highest degree of realism possible, the most appropriate model would be the "leaky integrate and fire". The author proposed an enhanced "leaky integrate and fire" model that a reasonable computational cost was capable of displaying the 20 neural behaviors analyzed [36]. The same author published a review on the hybrid models of spiking neurons [107].

Table 2. Computational cost in FLOPS of neural models.

Neural Models	FLOPS
Integrate and fire	5
Quadratic integrate and fire	7
Integrate and fire or bust	13
Izhikevich	13
Hodgkin-Huxley	1200

Piccinini and Bahar [108] presented an analysis of neural computation and computational theory of cognition. It was proposed that neurons did not use an analog or digital computation, but rather the neural computation was sui generis.

D'Angelo *et al.* [109] reviewed the realistic simulation strategies from the perspective of the research of brain diseases and neuro-robotics, using as example the cerebellar networks.

Wim van Drongelen [110] presented an overview of the different computer models of neurons and networks, focusing first on the Hodgkin-Huxley model, and subsequently on the activity of neural networks. Finally, the author analyzed how these models were used in the study of diseases such as epilepsy.

The authors of this review [111] performed a classification of neural models according to two criteria: the complexity of the model and workflow management (bottom-up and top-down).

Brette *et al.* [112] performed a review of the strategies of simulation of spiking neural networks and algorithms implemented. The advantages and disadvantages of different open-source simulators were analyzed. In addition, various types of networks of spiking neurons were implemented in different simulators and the code used was described.

2.1.4. Neuromorphic Chips

Chicca *et al.* [81] conducted a review of the implementations of neurons and synapses in silico used to build autonomous cognitive systems, and made a description of the electronic circuits that emulated the brain.

Hasler and Marr [113] showed an analysis of analog neuromorphic hardware systems and compared them with the digital and biological systems.

Indiveri *et al.* [80] described the "building block" and the most common techniques to implement neurons in silico. Moreover, different design methodologies were compared and the experimental results demonstrated their features.

Misra and Saha [114] conducted a review of hardware implementations of neural networks, classifying them into: digital, analog, hybrid and FPGA. Models of ANN, hardware designs and applications were discussed.

Xue [115] presented the recent developments in analog computation. These systems were explained from their basic elements, such as memory and arithmetic elements, to architecture and system design.

Boahen *et al.* [116] summarized the modeling of the nervous system and the advantages of the analog neuromorphic computing chips.

2.1.5. Books

There are a vast number of books on simulation/ emulation of the brain. Some of the most optimistic authors claimed that in the coming decades it would be possible to simulate a human brain in its entirety and that this simulation would replicate a real brain [2, 117-120]. However, other authors believe that it will be impossible to simulate the brain on a Turing machine [89, 121-123].

2.2. Classification and Characteristics of the Models

The classification of the types of works and computational models that have been discussed in this article is shown in Fig. (**3**). As mentioned in the Introduction section, the classification is based on the type of signal treatment of the computational model: digital, analog or hybrid.

Considering the reviews described above and various existing studies, Table **3** shows an overview of key features of each work/project discussed in this paper. 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 project funding for the European universities is 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} [1]. It should be noted that this simulation is not expected to be realistic and uses very simplified neuronal models. Furthermore, the simulation runs x1542 times slower than real time and 1.5 million BlueGene/Q cores [124] 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 [125], although there are progressively more software models using built-in spiking neurons [112] that simulate action potentials. In the case of realistic models, usually present ion channels responsible for the spike generation. The Hodgkin- Huxley model [17] requires more computational resources because it simulates Ca^{+2}, K^+ and Na^+ currents. It is used in the HBP [37], Neurogrid [62] and NeuroDyn [126]. 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 [20] and compartment models [127] are used. For more information about these models, please refer to [128]. 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 [38], SpiNNaker [61] and SyNAPSE [60]. 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 1.37×10^{14} simulated synapses [25], 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 [95, 96] 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. [36]. 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 [78] or GPU clusters [79]. Moreover, others use neuromorphic chips specifically designed to process information emulating the brain, both digital (SpiNNaker [61], TrueNorth [60]) and analog (HICANN [64]), and even hybrid (Neurogrid [62], Zeroth [97]). 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 described in the next sections of this paper 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.

Fundamental and most recent papers about the projects/models: some fundamental papers, where the projects were announced for the first time, are presented, along with those showing the most recent developments.

The following sections outline some recent developments for some of the most important projects.

Table 3. Overview of key features of relevant projects discussed in this paper. Objectives: 1. Help to understand some aspects of the brain - Computational Neuroscience; 2. Develop brain models to process large amounts of data - Artificial Intelligence; 3. Create processing hardware architecture inspired by the brain, neuromorphic chips; 4. Build devices to help disablepeople.

<table>
<tr><th colspan="2">Projects</th><th>Project name</th><th>Institution</th><th>Num. neurons</th><th>Type of neurons</th><th>Simulated synapses</th><th>Objectives</th><th>Project duration</th><th>Refs.</th></tr>
<tr><td rowspan="4">Digital Models</td><td rowspan="2">Software</td><td>Human Brain Project</td><td>European Union</td><td>10^6</td><td>Hogdking & Huxley</td><td>$5x10^8$</td><td>1, 2, 3, 4</td><td>2013-2023</td><td>[37, 129-140]</td></tr>
<tr><td>SPAUN</td><td>Univ. Waterloo</td><td>$2.5x10^6$</td><td>Leaky integrate-and-fire</td><td>10^{12}</td><td>1</td><td>2012 –</td><td>[38, 141-150]</td></tr>
<tr><td rowspan="2">Hardware</td><td>SpiNNaker</td><td>Univ. Manchester</td><td>$2.5x10^5$</td><td>Point neuron models, leaky integrate-and fire, Izhikevich's models</td><td>$8x10^7$</td><td>1, 2, 3, 4</td><td>2005 –</td><td>[61, 161-184]</td></tr>
<tr><td>SyNAPSE</td><td>IBM</td><td>10^{11}</td><td>Improved leaky integrate-and-fire.</td><td>10^{14}</td><td>2, 3</td><td>2008 –</td><td>[25, 60, 185-195]</td></tr>
<tr><td colspan="2" rowspan="3">Analog Models</td><td>BrainScales</td><td>European Union</td><td>$4x10^6$</td><td>Adaptive exponential integrate and fire neurons</td><td>10^9</td><td>1, 2, 3</td><td>2011-2015</td><td>[64, 132, 206-208]</td></tr>
<tr><td>HiAER-IFAT</td><td>Univ. California at San Diego</td><td>250.000</td><td>Integrate-and-fire with two compartments for neuron</td><td>$5x10^6$</td><td>1, 2, 3, 4</td><td>2004 –</td><td>[209-213]</td></tr>
<tr><td>NeuroDyn</td><td>Univ. California at San Diego</td><td>4</td><td>Hogdking & Huxley. 384 parameters and 24 channels.</td><td>12</td><td>1</td><td>2004 –</td><td>[209-213]</td></tr>
<tr><td colspan="2" rowspan="3">Hybrid Models</td><td>Neurogrid</td><td>Stanford University</td><td>10^6</td><td>Quadratic integrateand-fire somatic compartment + Dendritic compartment model with 4 Hogdking & Huxley channels</td><td>10^9</td><td>1, 3, 4</td><td>2007 –</td><td>[62, 221-226]</td></tr>
<tr><td>BRAIN Initiative</td><td>Qualcomm</td><td>not public</td><td>not public</td><td>not public</td><td>1, 2, 3</td><td>2013 –</td><td>[63, 97, 227]</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

3. DIGITAL BRAIN COMPUTATIONAL MODELS

On the one hand, studies and projects that build digital models should be pointed out, where simulation is performed using specific software and, on the other hand, those using neuromorphic hardware. As mentioned in the Introduction section, the specific simulation software is run in parallel by CPUs or GPUs. Those which use digital neuromorphic hardware build models mainly by means of special integrated digital circuits and inspired by the architecture of the brain networks.

3.1. Software Simulation

3.1.1. The Human Brain Project

The European Union approved in 2013 the Human Brain Project (HBP) project as part of the FET Flagship with a budget of 1000 million euros [37, 129, 130]. It is a continuation of the Blue Brain Project, which began in the École Polytechnique Fédérale de Lausanne (EPFL), Switzerland, in 2005 and whose principal investigator was Henry Markram [78, 131]. The strategic project partner is IBM and currently they use the Blue Gene/Q supercomputer [124] for the simulations. But they also collaborate with other projects to develop neuromorphic chips (FACETS [132], BrainScaleS [64] and SpiNNaker [61]). In March 2015 the Mediation Report [133] was published, which was commissioned by the EU following an open letter signed by more than 800 researchers [134]. They criticized the structure and leadership of the project, as well as the narrow focus on the brain simulation objective, since the cognitive and neuroscience systems were left aside. From our perspective, one of the main problems of the HBP is the little importance granted to the glial cells in the project. Here it is a brief cite from the HBP website [135]:

"What about glia? Building unifying brain models means taking account of every aspect of biology. Glia are a key component of the brain, supporting neurons and controlling metabolism and blood flow. This will be a step-by-step process. First we will build models that include the basic molecular machinery of cells and synapses. Then we will use detailed synchrotron scans to map out the detailed vasculature of the brain. Finally we will be able to model glia."

3.1.1.1. Objectives

The main objectives of the project are the following:

- Simulate the brain
- Develop Brain-Inspired Computing and Robotics
- Develop Interactive Supercomputing
- Map Brain Diseases
- Perform Targeted Mapping of the Mouse Brain and the
- Human Brain
- Develop a Multi-Scale Theory for the Brain
- Catalyse Revolutionary New Research
- Drive Collaboration with other Research Initiatives
- Drive Translation of HBP Research Results into Technologies,
- Products and Services
- Pursue a Policy of Responsible Research and Innovation

3.1.1.2. Structure

This project involves 112 partners in 24 countries and has 256 leading scientists. Due to the large size of the consortium, the project has been subdivided into 13 sub-projects:

SP1 - Strategic Mouse Brain Data
SP2 - Strategic Human Brain Data
SP3 - Cognitive Architectures
SP4 - Theoretical Neuroscience
SP5 - Neuroinformatics
SP6 - Brain Simulation
SP7 - High Performance Computing
SP8 - Medical Informatics
SP9 - Neuromorphic Computing
SP10 - Neurorobotics
SP11 - Applications
SP12 - Ethics and Society
SP13 – Management

3.1.1.3. Information and Communications Technology Platforms

To promote collaboration, the HBP will develop six platforms of information technology and communications that will contribute to the development of different types of computer models:

- Brain Simulation: building ICT models and simulations of brains and brain components. The HBP uses parallelized versions of Neuron [75], STEPS [136] and NEST [77]. The simulations were run in parallel on multiple processors. The behavior of axons, dendrites, cell bodies, is modeled with all kinds of internal details that mimic the real neurons. Each neuron is represented by hundreds of separate compartments, each producing an output based on ion channels and adjacent regions. To compute the potential of each compartment the Hodgkin-Huxley equations are used, which consider only realistic values of the parameters. The models used are based on anatomical and electrophysiological experimental data. To validate the models they use new data that have not been used to create the model. They consider the cortical microcolumn (MCC) as the smallest functional unit of the neocortex [137-139]. The MCC is a cylinder with a diameter of 0.5 mm and height of 2 mm. For each cylinder, there are 60,000 neurons in humans and 10,000 neurons in rats. The HBP roadmap established that by 2018 it is expected that a complete rodent brain is simulated at the cellular level. Another aim is to create molecular level simulations to test the effectiveness of different drugs in order to cure diseases of the nervous system, including Alzheimer's or Parkinson. The ultimate goal for 2023 is to create a simulation of the entire human brain with realistic multiscale models.

- Neuromorphic Computing: ICT that mimics the functioning of the brain. Furthermore, with respect to neuromorphic models, this platform is based on the FACETSBrainScaleS projects for Neuromorphic Physical Model (NM-PM), and Spinnaker for Neuromorphic Many-Core system (NM-MC). The NM-PM incorporates 8-inch silicon wafer in 180nm process technology with 200,000 realistic neurons and $50x10^6$ synapses. The ML-MC system with a chip can simulate 16,000 neurons with 8 million synapses in real time and consuming 1W. For future versions of these systems, t high-density packaging technologies, and novel techniques of Computer Aided Design are currently under development.

- Neuroinformatics: a data repository, including brain atlases.

- Medical Informatics: bringing together information on brain diseases.

- Neurorobotics: testing brain models and simulations in virtual environments.

- High-Performance Computing: hardware and software to support the other platforms.

3.1.1.4. Cajal Blue Brain Project

The Spanish contribution [140] to the Blue Brain Project should also be mentioned, which began in January 2009, led by the Polytechnic University of Madrid (UPM) and the Cajal Institute of the Spanish National Research Council (CSIC). The project objectives are: (1) decode the detailed map of synaptic connections in a cortical column and rebuild all components, (2) investigate the hypothesis that some diseases are related to cortical columns, (3) develop new methods for processing and analyzing experimental data and (4) develop methods for the study of neural functions using graphical tools and visualization techniques. A secondary objective is to understand the involvement of glial cells and blood vessels in the organization of the cortical column.

3.1.2. SPAUN

Semantic Pointer Architecture Unified Network (SPAUN) [141, 142] is the only simulation able to perform a variety of perceptual, motor and cognitive tasks in the real world without any change in the system [143-145]. It has 2.5 million neurons and 60 million synapses, and uses a spike-timing- dependent plasticity learning rule. It takes approximately 2.5 h of simulation time to generate 1 s of behavior on a high-end workstation. It uses the neural engineering framework (NEF) [146-148], a mathematical theory that provides methods for systematically generating biologically plausible spiking networks to implement non-linear and linear dynamical systems. Besides, the Semantic Pointer Architecture (SPA) [149] is proposed, a hypothesis regarding some aspects of the organization, function, and representational resources used in the mammalian brain. A software tool known as Neural ENGineering Objects (Nengo) [150] was developed, which allows for the synthesis and simulation of neural models efficiently on the scale of SPAUN, and provides support for constructing models using the NEF and the SPA.

This is a top-down simulation in which the objective is to perform different tasks without any change in its structure, rather than achieving fidelity between the simulated neurons and the real ones. The human brain regions and their functions were simulated (Fig. **4**): PPC, posterior parietal cortex; M1, primary motor cortex; SMA, supplementary motor area; PM, premotor cortex; VLPFC, ventrolateral prefrontal cortex; OFC, orbitofrontal cortex; AIT, anterior inferior temporal cortex; Str, striatum; vStr, ventral striatum; STN, subthalamic nucleus; GPe, globus pallidus externus; GPi, globus pallidus internus; SNr, substantia nigra pars reticulata; SNc, substantia nigra pars compacta; VTA, ventral tegmental area; V2, secondary visual cortex; V4, extrastriate visual cortex.

SPAUN can perform 8 different tasks: (1) Image recognition; (2) Copy drawing; (3) Reinforcement Learning (RL); (4) Serial Working Memory; (5) Counting; (6) Question answering; (7) Rapid variable creation and (8) fluid reasoning.

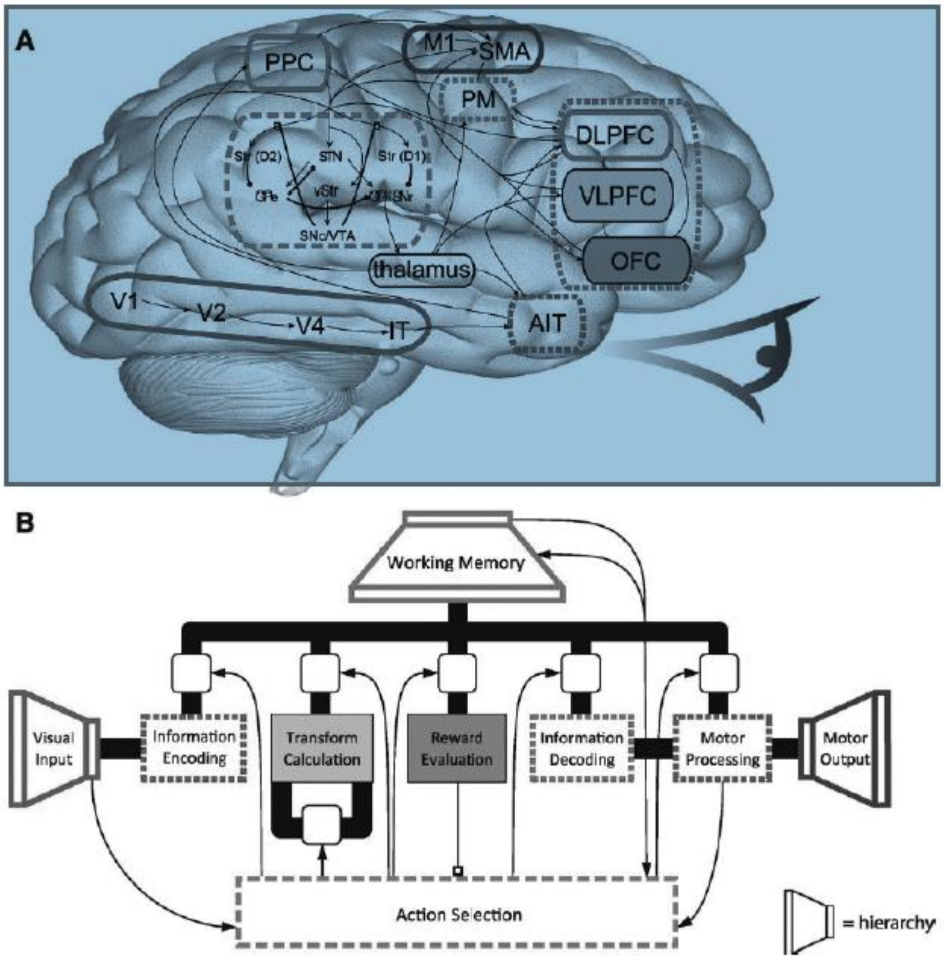

Fig. (4). Anatomical and functional architecture of Spaun [141]. (**A**) The anatomical architecture of Spaun shows the major brain structures included in the model and their connectivity. (**B)** The functional architecture of Spaun.

3.1.3. Artificial Neural Networks

It is known that ANN or connectionist systems are digital models of the brain. The connectionist branch of Artificial Intelligence tries to emulate the brain (its elements and connections), fundamentally, to process information. The connectionist systems are oriented towards solve real world problems, just like the human brain does. These systems are trained to solve different kind of problems (classification, prediction, regression, pattern recognition, etc.) [151-153]. The advances in these systems help making them more effective and efficient in their tasks. Some researchers try to achieve this goal by mimicking the brain. They build models inspired by the latest discoveries in Neuroscience, not only related to the neurons, but also to glia cells and their role in the information processing. There is a double advantage in using this line of research. On the one hand, Computer Science benefits from the development of systems with new information processing capacities. On the other hand, Neuroscience develops even further because these systems allow modeling in computers behaviors that are not yet fully understood by the neuroscientific community.

The main recent breakthrough in this field was made by DL [39, 40, 42-46]. This refers to a brain-inspired technique used to create connectionist systems with several layers, allowing a great level of abstraction, similar to that observed in the visual system of the brain [19, 154-156]. DL is a class of machine-learning algorithms that allow computational models composed of multiple processing layers to learn representations of data with multiple levels of abstraction. Layers that have been used in DL include hidden layers of an ANN and sets of complicated propositional formulas. Another recent ANN model that is expected to get closer to brain function is Spike Neural Networks (SNN) [112, 157- 160]. It falls into the third generation of neural network models, increasing the level of realism in a neural simulation. In addition to neuronal and synaptic state, SNNs also incorporate the concept of time into their operating model. The idea is that neurons in the SNN do not fire at each propagation cycle (as it happens with typical multi-layer perceptron networks), but rather fire only when a membrane potential – an intrinsic quality of the neuron related to its membrane electrical charge – reaches a specific value. When a neuron fires, it generates a signal that travels to other neurons which, in turn, increase or decrease their potentials in accordance with this signal.

Connectionist systems must be trained with considerable amounts of data and subsequently they are tested with many real data. It is a process that requires multiple executions and thousands of simulations. This process requires a high computational consumption. Thus, multi-processor supercomputers or clusters of machines are used for running tests and simulations. Therefore, this is a field in which the parallel computing is justified. Note here the use of the GPUs for running connectionist systems. The general-purpose computing on graphics processing units (GPGPU) is a relatively recent trend in computer engineering research. GPUs are coprocessors that have been heavily optimized for computer graphics processing. The computer graphics processing is a field dominated by data parallel operations, including linear algebra and matrix operations. At first, GPGPU programs generally used graphics API to run programs. However, several new programming languages and platforms have been constructed for general-purpose computing on GPUs. This situation was used to run thousands of simulations with connectionist systems. For example, for their large computational needs the simulation of ANN with DL on GPUs [79] is commonly employed.

3.2. Hardware

3.2.1. SpiNNaker

SpiNNaker is a project of the University of Manchester, whose principal investigator is Steve B. Furber [161]. Within this project, chips which contain many small CPUs were produced. Each CPU is designed to simulate about 1000 neurons, such as leaky integrate and fire or Izhikevich's model, which communicate spike events to other CPUs through a network package. Each chip consists of 18 ARM968 processors, one of them acting as a processor monitor. In 2015 a cabinet with 5760 chips was created, which can simulate 100 million point neurons with approximately 1000 synapses per neuron [162]. The chips are connected with adjacent chips by 2-dimensional toroidal mesh network and each chip has 6 network ports [163-165]. This system is expected to mimic the features of biological neural networks in various ways: (1) Native parallelism - each neuron is a primitive computational element within a massively parallel system [166]; (2) Spiking communications - the system uses AER, thus the information flow in a network is represented as a time series of neural identifiers [167]; (3) Event-driven behavior - to reduce power consumption the hardware was put in "sleep" mode, waiting for an event [168, 169]; (4) Distributed memory - this system uses memory local to each of the cores and an SDRAM local to each chip; (5) Reconfigurability - the SpiNNaker architecture allows on-the-fly reconfiguration [170].

In order to configure a large number of cores, with millions of neurons and synapses, PACMAN [171] was developed. It is a software tool that helps the user to create models, translate and execute in the spinnaker. This allows the user to work with neural languages like PyNN [172] or Nengo [150, 173].

Until 2013 the SpiNNaker presented the possibility to simulate simple models in real-time on the SpiNNaker neuromimetic architecture. However, such models were "static", the algorithm performed was defined at design time. In 2013 a paper [174] was published, in which a novel learning rule was presented, describing its implementation into the SpiNNaker system, which enables models designed with the NEF to learn the function to be performed using a supervised framework. The authors showed that the proposed learning rule, belonging to the Prescribed Error Sensitivity class, is able to learn effectively both linear and non-linear function.

The main applications of this piece of neuromorphic hardware are:

- Interface with Nengo (SPAUN): using NEF [146] functions and dynamic systems can be encoded in networks of spiking neurons, allowing to create complex cognitive systems such as SPAUN [141]. Spinnaker has been connected to Nengo [175], enabling users to create neural networks and specify the functions that are computed.

- Deep Belief Networks: networks of deep learning may be implemented, obtaining an accuracy rate of 95% in the classification of the MNIST database of handwritten digits. 0.06% less than the software implementation is obtained, but the consumption is only 0.3 W [176].

- Convolutional Neural Networks: they possess a "weight sharing" property, so that many neuron-to-neuron connections share the same weight value. Therefore, a much reduced amount of memory is required to define all synaptic weights, which can be stored on local SRAM DTCM (data-tightly-coupled-memory) at each ARM core. This way, DRAM can be used extensively to store traffic data for off-line analyses. A 5 layers deep learning network is implemented to recognize symbols which are obtained through a Dynamic Vision Sensor (DVS). Each ARM core can accommodate 2048 neurons. The full chip could contain up to 32,000 neurons [177].

- Interface with AER sensors: in 2015 a paper with a new framework on the SpiNNaker platform has been published, which allows simulation of spiking networks and plasticity mechanisms using a completely asynchronous and event-based scheme running with a microsecond time resolution [178]. In collaboration with the Microelectronics Institute of Seville (Instituto de Microelectronica, Seville, Spain) the authors have connected a silicon retina to SpiNNaker using an FPGA [179]. Analogous interfaces with AER sensors have been developed in collaboration with the Institute of Neuroinformatics (Zurich, Switzerland; using the DVS [180] and the ‘‘silicon cochlea’’ [181]), with the Biology Group at the University of Osaka (Osaka, Japan; using a sensor inspired by the sustained and transient responses of the retina [182]), and with the Institute of Vision (Paris, France; using the ATIS silicon retina [183]).

- Integration with robotic platforms: the robotic platform can be used with PyNN [172] or Nengo [150, 173], whereas the system is automatically configured with PACMAN [171], enabling message transmission to and from the robot and the sensors through a small customized interface board [184]. The robot is a customized omnidirectional mobile platform, with embedded low level motor control and elementary sensory systems, developed by the Neuroscientific System Theory group of the Technische Universität München (Munich, Germany). The overall system is a standalone, autonomous, reconfigurable robotic platform with no personal computer in the loop.

- Simulation in real time of cortical circuits: 4 SpiNNaker chips are used to simulate 10,000 spiking neurons and 4 million synapses in real time and consuming only 100 nJ per neuron per millisecond [49].

Some future plans for the SpiNNaker project are [162]: (1) work with the Human Brain Project; (2) prove that it can withstand SPAUN in real time, for which approximately 32,832 processors (36 boards spinnaker) would be needed; (3) build the final extension that would house a system with 10 cabinets and a total of 1,036,800 ARM processors.

3.2.2. SyNAPSE

The DARPA SyNAPSE initiative (System of Neuromorphic Adaptive Plastic Scalable Electronics) selected and funded the proposal “Cognitive Computing via Synaptronics and Supercomputing (C2S2)” of the Cognitive Computing Group at IBM Research Lab Alamaden directed by Dharmendra Modha [185]. The project is based on the design and creation of a neuromorphic chip called TrueNorth, a non-von Neumann, modular, parallel, distributed, event-driven, scalable architecture- inspired by the function, low power, and compact volume of the organic brain (Fig. **5**). It is a versatile substrate for integrating spatio-temporal, real-time cognitive algorithms for multi-modal, sub-symbolic, sensor-actuator systems [186]. Currently in the final phase of the project, the researchers have created a board with 16 TrueNorth neuromorphic chips, capable of simulating 16 million neurons and 4 billion synapses. In 2015 they planned to create a system with 128 chips and simulate 128 million neurons [187].

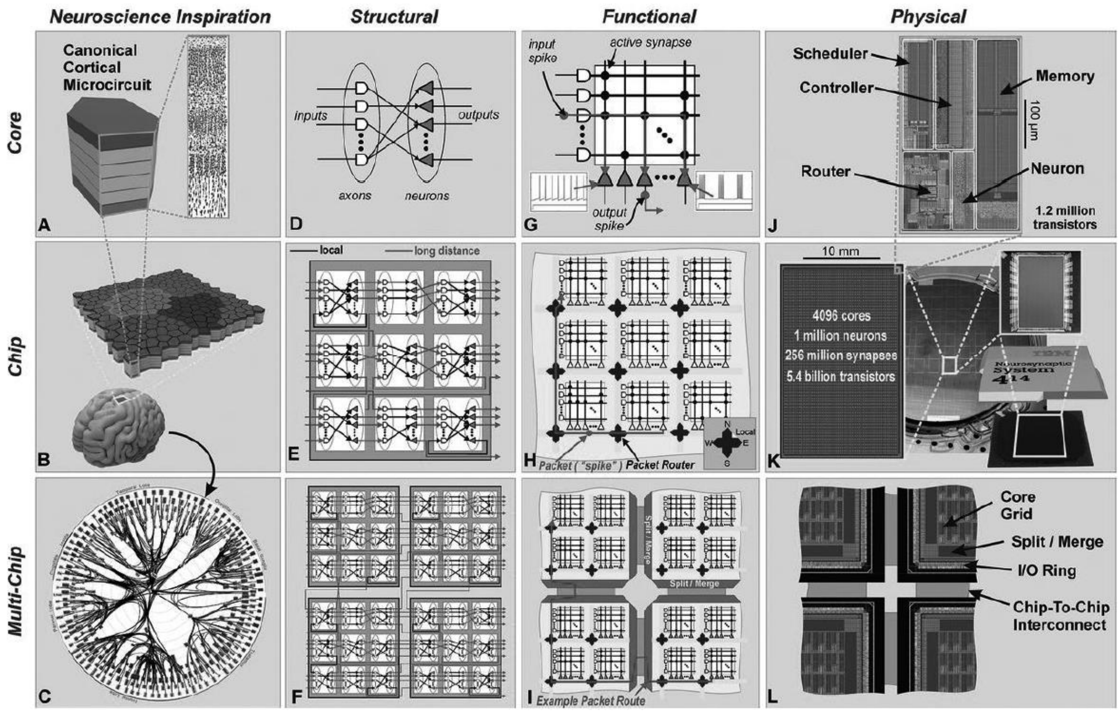

Fig. (5). TrueNorth architecture [185]. Panels are organized into rows at three different scales (core, chip, and multichip) and into columns at four different views (neuroscience inspiration, structural, functional, and physical).

The TrueNorth prototype was created in 2011 [188], and it was a neurosynaptic core with 256 digital leaky integrate-and-fire neurons and up to 256000 synapses. Each core brings memory ("synapses"), processors ("neurons"), and communication ("axons") in close proximity, wherein intercore communication is carried by all-or- none spike events. This allows an efficient implementation of a parallel asynchronous communication and AER. In 2012 Compass [189] was developed, a simulator to design neural networks to be implemented in the neuromorphic chip. Compass is a multithreaded, massively parallel functional simulator and a parallel compiler. It uses the C++ language, sends spikes event via MPI communication and uses OpenMP for thread-level parallelism. A simulator for GPGPU [190] was also developed. Modha's team simulated in 2007 the brain of a rat in an IBM BlueGene/L supercomputer [191]. In 2010 they simulated a monkey brain [192] in IBM BlueGene/P supercomputers from a network map of long-distance neural connections in the brain obtained with 410 anatomical studies (Collation of Connectivity data on the Macaque brain) [132]. Later that same year, they published the results of a simulation with Compass of 2048 billion neurosynaptic cores and $5{,}4 \times 10^{11}$ neurons and $1{,}37 \times 10^{14}$ synapses [25]. The execution was x1542 times slower than real time, and 1.5 million Blue Gene / Q supercomputers were needed.

3.2.2.1 Neuron Model

The chip uses a simple digital spiking neuron model that is versatile and reconfigurable [194]. This allows one-to-one equivalence between hardware and simulation, using only 1272 ASIC gates. The classic model of leaky integrate and fire model was improved by adding: (a) configurable and reproducible stochasticity to the input, the state, and the output; (b) four leak modes that bias the internal state dynamics; (c) deterministic and stochastic thresholds; and (d) six reset modes for rich finite-state behavior. Moreover, over 50 neural behaviors were included in a library, to hierarchically compose complex computations and behaviors. This neural model can qualitatively replicate the 20 most biologically relevant behaviors of neuronal dynamics. The chip allows using binary code, populations, time-to-spike code and code rate.

3.2.2.2 Programming Paradigm

A TrueNorth program is a complete specification of a network of neurosynaptic cores, and all external inputs and outputs to the network, including the specification of the physiological properties (neuron parameters, synaptic weights) and the anatomy (inter- and intra-core connectivity) [186]. The programming paradigm has four levels: (1) a corelet, namely an abstraction that represents a TrueNorth program that only exposes external inputs and outputs while encapsulating all the other details of the network of neurosynaptic cores; (2) an object-oriented Corelet Language for creating, composing, and decomposing corelets; (3) a Corelet Library that acts as an ever-growing repository of reusable corelets from which to compose new corelets; and (4) an end-to-end Corelet Laboratory that is a programming environment that integrates with the TrueNorth architectural simulator, called Compass, and supports all aspects of the programming cycle from design, through development, debugging, and into deployment.

The library is a repository of consistent, verified, parameterized, scalable and composable functional primitives. The corelets currently in the Corelet Library include scalar functions, algebraic, logical, and temporal functions, splitters, aggregators, multiplexers, linear filters, kernel convolution (1D, 2D and 3D data), finite-state machines, non-linear filters, recursive spatio-temporal filters, motion detection, optical flow, saliency detectors and attention circuits, color segmentation, a Discrete Fourier Transform, linear and nonlinear classifiers, a restricted Boltzmann machine, a liquid state machine, and more.

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3.2.2.3 Algorithms and Applications

Algorithms which include convolution networks for spatial feature extraction, spectral content estimators for time-domain to frequency-domain conversion, liquid state machines for feature extraction in time-varying signals, restricted Boltzmann machines (RBMs) for spatial feature extraction, hidden Markov models as an example of finite-state machines, looming detectors, temporal pattern matching, and various classifiers (logistic regression, backpropagation, stackable covariance-based) were implemented. The same corelet algorithm is often used across multiple applications, and multiple corelet implementations are possible for the same algorithm, showcasing the composability and flexibility of corelet construction [195].

TrueNorth was used in seven applications that include speaker recognition, music composer recognition, digit recognition, sequence prediction, collision avoidance, optical flow, and eye detection.

3.2.3. Other Projects

This section summarizes some smaller-scale projects, whose goals are also to develop hardware models with applications in various areas.

- The Robotics and Computer Laboratory Technology at the University of Seville [83] has been dedicated, since 1984, to Robotics, Neuromorphic Engineering, Architecture Embedded Systems and Computer Networks. The group began its work developing neuromorphic chips in 2001 within the VICTOR project (Vision by convolutions in real time) [196] that ended in 2005. Between 2002 and 2006 CAVIAR (AER vision Convolution architecture) [197] was developed, a massively parallel hardware implementation for recognizing and tracking objects in real time. The system uses an asynchronous communication that employs AER. The system simulates 45,000 neurons, 5 million synapses and performs 12,000 million synaptic operations per second, which enables it to recognize and track objects with milliseconds latencies. In 2012 two projects were completed, VULCANO (ultra-fast frame-less vision by events. Application to automotion and anthropomorphic cognitive robotics) [198] which was begun in 2010, and SAMANTA I and II (Multi-chip address-event-representation Vision system for robotics platform I & II) [199] which was begun in 2003. Currently, the group is working on the BIOSENSE project (Bioinspired event-based system for sensory fusion and neurocortical processing) [200] which aims to create a robotic platform based on modular AER technology. The system emulates the hierarchy of the cerebral cortex to integrate sensory information received from several 3D vision cameras and hearing cochlea, and produces a motor response in the order of milliseconds. The system used spike time dependent plasticity learning (STDP) techniques. The project is aimed at demonstrating two possible applications for this technology. First, monitoring the behavior of the driver inside the vehicle and subsequently a robot to pick up and manipulate objects moving at high speed.

- The University of Cambridge carried out the BIMPA project (Biologically-inspired massively-parallel architectures) [82], which was begun in 2008 and ended in June 2014. The project's goal was to create a machine with a large cost-effectiveness to investigate the emergent behaviors, adaptability and fault tolerance of such systems. To this end, Bluehive [201-203] was developed, a system consisting of 64 FPGA that can simulate 64,000 Izhikevich neurons, each with 1000 synapses.

- Ahmed Hemani and Nasim Farahini published a paper in 2013 on the concept of a new customized multichip supercomputer called BRIC [84]. The technology is estimated to be available between 2015 and 2020 [204], and it would be used to simulate real-time models of the complete human brain, using spiking Bayesian Confidence Propagation Neural Network (BCPNN). This system could be an improvement in efficiency from 2 to 3 orders of magnitude compared to the general-purpose supercomputer, due to innovation in algorithms, architecture, customization and 3D integration [205].

4. ANALOG BRAIN COMPUTATIONAL MODELS

4.1. BrainScales

The BrainScales (Brain-inspired multiscale computation in neuromorphic hybrid systems) project [64] was funded by the EU, it was started on January 1, 2011 and ended on March 31, 2015. It involved 19 research groups from 10 European countries and represents a continuation of the FACETS project (Fast Analog Computing with Emergent Transient States) [132] that took place from 2005 to 2010. First, the researchers developed a neuromorphic ASIC chip called "Spikey". Subsequently, they created HICANN (High Input Count Analog Neural Network) [206], a multi-chip CMOS wafer that employs adaptive exponential integrate and fire neural models. They developed a software tool to automatically translate a PyNN design into hardware implementation optimized for HICANN [207]. In a wafer 200,000 neurons and 50 million synapses can be simulated, 10,000 times faster than real time. The chip allows short- and longterm plasticity.

The PAX (Plasticity Algorithm Computation System) project [208] was part of the FACETS projects and later of BrainScales. This project involved Sylvie Renaud and Sylvain Saïghi (Université de Bordeaux), who develop a hybrid brain model. They collaborated with Karlheinz Meier’s group from the University of Heidelberg to develop and validate these rules of synaptic plasticity, especially STDP, for their use in HICANN.

Currently, BrainScales is part of the HBP, and a system with 20 wafers in 65nm CMOS will be created by 2017, which is expected to simulate 4 million neurons and one billion synapses. By 2022, the researchers’ intention is to create a system with 500 or 5,000 wafers to simulate between 500 and 5,000 billion neurons.

4.2. HiAER-IFAT & NeuroDyn

A group of researchers at the University of California, San Diego, have created two different neuromorphic chips, HiAER-IFAT (Hierarchical AER Integrate and Fire Array Transceiver) [209-210], which can simulate 250,000 neurons, and NeuroDyn [212], which emulates four neurons and 12 synapses with a great level of detail. NeuroDyn uses the Hodgkin-Huxley model with 384 parameters in 24 channels. They have also proposed a memristor for spiking neurons [213].

The IFAT chips have several applications: Laplacian filters to isolate edges in images, spatial filters to process spikes in training an artificial retina [36]. The NeuroDyn chip allows simulating the patch-clamping experiments performed in real neurons.

4.3. Other Projects

The Institute of Neuroinformatics at the University of Zurich sought to create cognitive neuromorphic VLSI systems for specific applications. In 2009 the Neuromorphic Cognitive System group [214] was established. The director is Giacomo Indiveri, who edited a remarkable book, "Event Based Neuromorphic Systems" [215]. Nowadays this group participates in several projects based on neuromorphic chips: neuroP (Neuromorphic Processors), SCANDLE (acoustic SCene ANalysis for Detecting Living Entities), EMorph (Event-Driven Morphological Computation for Embodied Systems), nAttention (Neuromorphic Attention), SoundRec (Real-time sound recognition using neuromorphic VLSI), Optic Flow (Implementation of biomimetic control principles using neuromorphic optic flow sensors) and other long-term projects. The research group has published extensively on the developed systems: a neuromorphic vestibular system [216], Brain Machine Interface [217], Recurrent Neural Networks [218], autonomous robots [219] and a reconfigurable chip for online learning [220].

5. HYBRID BRAIN COMPUTATIONAL MODELS

5.1. Neurogrid

The Neurogrid [221] is a project developed by Stanford University [62], led by Kwabena Boahen. It is a neuromorphic system aimed at simulating large-scale neural models in real time. It is able to simulate a million neurons with a trillion synaptic connections in real time, using 16 neurocores (each NeuroCore simulates 65,000 neurons) integrated into a plate that consumes 3 Watts. The Neurogrid uses a two-level simulation model for neurons. A quadratic integrated-and-fire model is employed for the somatic compartment. Dendritic compartments are modeled with up to four Hodgkin- Huxley channels [17]. The system emulates all the neural elements (axonal tree, synapses and dendritic tree) with shared electronic circuits except the soma (comparator), so the number of synapses is maximized. In addition, it is hybrid because all electronics are analog, except for the axonal trees to optimize energy efficiency. The neural arrays are interconnected in a multicast tree network to maximize performance [222, 223].

The architecture of shared dendrites and the tree router topology can be fully exploited by neural models that meet two requirements: firstly, they should be arranged in layers so that neighboring neurons in the same layer have essentially the same inputs as the cortical maps feature. This allows using shared dendrites. Secondly, they should be organized into columns so that neurons at corresponding locations, in different layers, have translation-invariant connectivity, as in cortical columns.

A limitation of the architecture of shared dendrites involves the lack of synaptic plasticity because neighboring neurons receive the same input. But Neurogrid architecture also supports shared synapses, allowing the modification of the individual weights of the connections, stored on the motherboard RAM, using STDP.

The Neurogrid was used to control an articulated robot in task-space [224]. NEF is also used to perform mathematical computations [225]. In addition, NEF is employed to integrate the Neurogrid with BMI in an experiment with a rhesus monkey [226].

5.2. BRAIN Initiative

The BRAIN (Brain Research through Advancing Innovative Neurotechnologies) Initiative was presented by the US president, Barack Obama, in April 2013 [63]. The project aims to accelerate progress in Neuroscience through the development and application of innovative technologies. The participating researchers focused on understanding the brain function and finding new treatments for brain diseases.

Five federal agencies are involved in the project: FDA (Food and Drug Administration), IARPA (Intelligence Advanced Research Projects Activity), NIH, NSF (National Science Foundation) and DARPA (Defense Advanced Research Projects Agency).

In addition, foundations, universities and private companies are also collaborating. The Carnegie Mellon University is among the many universities involved. One of its goals is to seek ways to increase the multidisciplinary Neuroscience collaboration between engineering, computer science and biology. The researchers' aim is to unite Neuroscience and behavior through the application of machine learning, statistical and computational models. They also plan to commercialize new technologies and applications inspired by the brain.

One of the most important companies participating in this initiative is Google. It is collaborating with the Allen Institute for Brain Science to develop scalable computational solutions to make progress with regard to the scientific knowledge about the brain. Google has also started to collaborate with the Howard Hughes Medical Institute's Janelia Research Campus and other academic institutions. It is also developing the necessary software and infrastructure to analyze datasets of petabytes scale generated by the BRAIN initiative and the Neuroscience community.

Another prominent company is Qualcomm [97], which contributes to the BRAIN initiative with its experience in the field of wireless communication, necessary for future Neuroscience tools. They are also developing a neural simulator (Neuromorphic hardware) that enables large-scale simulations in real time to the development and analysis of neural models. Qualcomm has a co-development agreement with Brain Corporation [227], a company co-founded by Eugene Izhikevich and Allen Gruber in 2009. The company has already developed several robotic products inspired by the brain, bStem (Plate processor Qualcomm Snapdragon S4- Pro, sensors and cameras to serve as the robots' brains), BrainOs (operating system for robots based on supervised learning) and the robot eyeRover. Currently they are developing a digital neuromorphic chip that includes a platform called Zeroth which mimics the brain in terms of encoding and transmitting information with electrical spikes. Qualcomm's aim is to incorporate the processor into their chip to process information from various sensors and create intelligent devices. There are no public papers on the technical aspects of the chip.

6. COMPUTATIONAL MODELS WITH GLIA

So far there was no study including astrocytes in a neuromorphic chip. There were only realistic computational models [228-236] and connectionist ones [158] which have taken glial cells into account. Currently, there are two projects aimed at implementing astrocytes in neuromorphic chips, one is BioRC developed by the University of Southern California and the other project is carried out by the University of Tehran and University of Kermanshah (Iran). 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 [26-29], 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 [237, 238]. Furthermore, the ratio between neurons and glial cells varies in different brain regions (see Fig. **6**). 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 [1, 239]. 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.

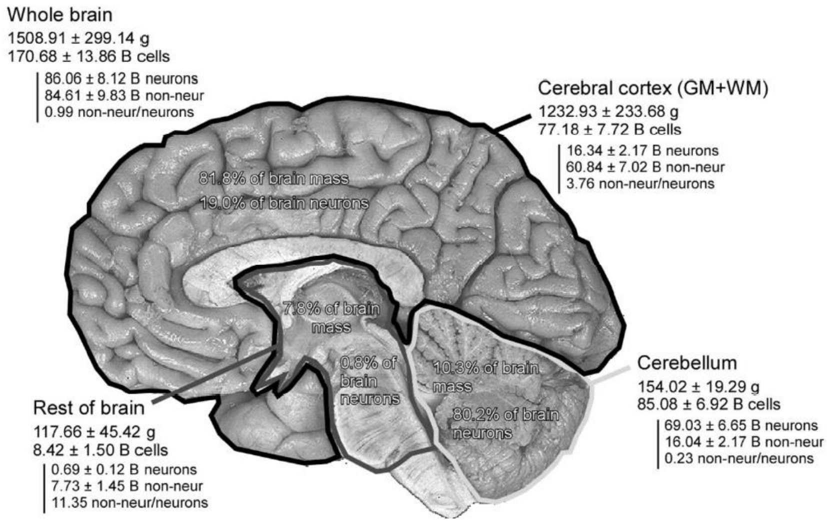

Fig. (6). Amount of neurons and glial cells in different brain regions.

6.1. BioRC

As part of the BioRC (Biomimetic Real-Time Cortex) project at the University of Southern California, in 2011 the researchers have developed the first CMOS neuromorphic circuit which emulates the microdomains glia [240], including several interconnected neurons in a small network. Astrocytes influence neuronal behavior, stimulating it to fire. Without the intervention of the glia, neurons would not have enough postsynaptic potential to shoot. The circuit represents a first order model of reciprocal feedback between neurons and astrocytes including gliotransmitters and neurotransmitters, and calcium concentrations induced in astrocytes.

This group has presented several papers with new behaviors of astrocytes. They simulate reception of neurotransmitters by astrocytes [241] and the slow inwards currents caused in the neurons by the astrocytes [242, 243]. The group is also developing BioRC carbon nanotube transistors [244-251] to simulate neuromorphic circuits. They also published a very interesting paper about the future of artificial brains and the challenges in mimicking the brain in order to build neuromorphic chips [36].

6.2. University of Tehran and University of Kermanshah

The University of Tehran and the University of Kermanshah (Iran) are collaborating in the development of a neuromorphic digital circuit to study neuron-astrocyte interactions [249-251]. The firing dynamics of the neuron is described by Izhikevich's model and calcium dynamics of each astrocyte is represented by a functional model proposed by Postnov and colleagues [252]. To implement the signals between neurons and astrocytes, the Single Constant Multiply (SCM) technique is used, as well as linear approximations, for a greater efficiency. The system was first simulated in MATLAB and then implemented into FGPA.

6.3. University of A Coruña

The RNASA-IMEDIR group from University of A Coruña (Spain) developed Artificial Neuron-Glia Networks (ANGN) [253-257]. The ANGN are software connectionist systems including artificial neurons and astrocytes (Fig. **7**). Artificial astrocytes control the neuron activation and modify the connection weights according to the neurons activation level. The design of ANGNs is based on feed-forward multilayer architectures which are totally connected, without backpropagation or lateral connections, and oriented towards classification and pattern recognition. The design of the first ANGNs was focused on solving classification problems by means of simple networks, i.e. multilayer networks, although further research may lead to the design of models in more complex networks.

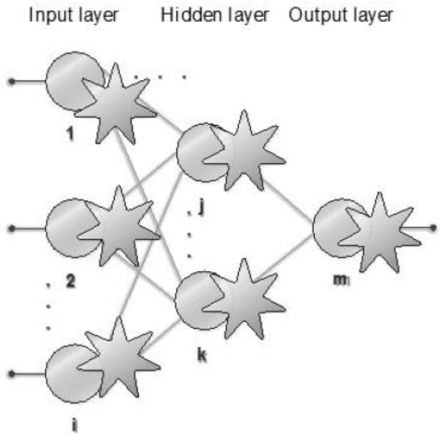

Fig. (7). Artificial neuron-glia network architecture.

CONCLUSION

This review has shown that there are a great variety of projects and models of the brain. Research centers around the world have taken great interest in brain modeling. The main area of interest pertains to the scientific, social and economic field. Parallel computing is crucial and extremely beneficial for these projects. The development of digital, analog and hybrid models is expedient and allows for advances in Neuroscience and Artificial Intelligence.

Of all the models reviewed, the SyNAPSE project should be pointed out for its great scope, results and applications already achieved. The TrueNorth chip could be the first neuromorphic chip commercialized. In addition, the SpiNNaker has already had various applications and a very interesting future lies ahead. Moreover, the BrainScaleS should also be emphasized for its speed and great potential within Neuroscience research.

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. The Computer Science and Artificial Intelligence fields are the areas which benefit mostly from brain modeling. 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.

Finally, there is growing interest in the study and simulation of the brain. This is due to the fact that the aging population and increased life expectancy will lead to age-related mental diseases such as dementia, Alzheimer's or Parkinson's, which affect more and more people. This will be a huge social problem and a high economic cost. Therefore, it is necessary to invest in brain research now in order to mitigate the future costs of mental diseases. On the other hand, this is a great opportunity for businessmen and entrepreneurs, as neuromorphic chips will support the third industrial revolution, setting a new programming paradigm. Nowadays, computers are tools that need to be programmed to perform a task;

however neuromorphic systems can learn tasks without specific programming. Thus, there is no need to know the steps to execute the task, solely to know which inputs and outputs are needed to train the system. This will then create systems characterized by an ever greater number of cognitive abilities, capable of surpassing the human brain.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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