Journal of Computer Sciences and Applications, 2019, Vol. 7, No. 1, 56-61
Available online at http://pubs.sciepub.com/jcsa/7/1/9
Published by Science and Education Publishing
DOI:10.12691/jcsa-7-1-9

Brain Science and Brain-inspired Artificial Intelligence: Advances and Trends

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Received November 09, 2019; Revised December 23, 2019; Accepted December 28, 2019

Abstract Brain science and brain-inspired artificial intelligence have been very significant areas. They have a wide range of applications including military and defense, intelligent manufacturing, business intelligence and management, medical service and healthcare, etc. Many countries have launched national brain-related projects to increase the national interests and capability in the competitive global world. In this paper, we introduce some concepts, principles, and emerging technologies of brain science and brain-inspired artificial intelligence; present their advances and trends; and outline some challenges in brain-inspired computing and computation based on spiking-neural-networks (SNNs). Specifically, the advances and trends cover brain-inspired computing, neuromorphic computing systems, and multi-scale brain simulation, brain association graph, brainnetome and the connectome, brain imaging, brain-inspired chips and brain-inspired devices, brain-computer interface (BCI) and brain-machine interface (BMI), brain-inspired robotics and applications, quantum robots, and cyborg (human-machine hybrids).

Keywords: *brain science, brain-inspired artificial intelligence, brain-inspired computing, brain association graph, brainnetome, brain imaging, brain-inspired chip, brain-computer interface, brain-inspired robot, cyborg*

Cite This Article: Lidong Wang, and Cheryl Ann Alexander, “Brain Science and Brain-inspired Artificial Intelligence: Advances and Trends.” *Journal of Computer Sciences and Applications*, vol. 7, no. 1 (2019): 56-61. doi: 10.12691/jcsa-7-1-9.

1. Introduction

The objective of neuromorphic engineering is to perform a brain-inspired computing architecture as an alternative paradigm to the von Neumann processor. A hardware-based SNN architecture was proposed for unsupervised learning with spike-timing-dependent plasticity (STDP) synapse array using flash memory synaptic array [1]. Cognitive computing generally fits in the probability method of statistics theory. It is a method that reasons with purposes, learns at scales, interacts with humans naturally, and enables to understand and analyze unstructured data [2].

Associative learning is a basic cognitive function by which discrete and often various percepts are linked together. Auditory- and multisensory-guided equivalence learning paradigms were introduced. Auditory, visual, and multi-sensory guided association learning are similarly effective for humans. The multi-sensory (audiovisual) stimuli elicits the best performance in cognitive learning. The test phase is generally a more difficult cognitive task compared with the acquisition phase, because multi-sensory information processing can make participants’ performance better [3].

Phase-change memory devices are useful for developing of memcomputing and neuromorphic applications due to proven large-scale manufacturability and the multi-level storage capability. By using electrical pulses, phase-change materials reversibly change from the crystalline to the amorphous phase. The resistance change due to the change of the structural phase configuration is used for storing information. The key of this conventional method lies in that phase-change materials are employed for both writing information and retrieving the stored information. The drawback of the method lies in their high defect density and highly disordered nature make them susceptible to highly undesirable electrical effects (e.g., noise and drift) though phase-change materials have very good phase-transition attributes [4].

Military Brain Science can help create a whole new "brain war" combat style. It deals with various brain activity patterns and influencing factors with the following goals: 1) understanding the brain—be familiar with risk factors of brain injury; 2) protecting the brain—targeted prevention of the brain damage; 3) monitoring the brain—monitoring brain functions using technology and devices; 4) injuring the brain—facilitating the development of types of weapons (such as explosion, light, magnetic) that injure the brain; 5) interfering with the brain—making brain dysfunction or a loss of control; 6) repairing the brain—performing the reconstruction of brain functions with advanced technology; 7) enhancing the brain-enhancing the brain function level of personnel who are involved in a special task using various means (e.g., magnetism, sound, and electricity); 8) simulating the brain—using methods such as brain-inspired robot intelligence; and 9) arming the brain—using brain-machine interfaces (BMIs) as a focus [5].

The main purpose of this paper is to introduce emerging technologies of brain science and brain-inspired artificial intelligence (such as brain-inspired chips, brain-inspired computing, neuromorphic computing systems, BCI and BMI, brain-inspired robotics, quantum robots, and cyborg); present their advances and trends; and point out some challenges in brain-inspired computing and SNNs-based computation.

2. Brain-inspired Computing, Neuromorphic Computing Systems, and Multi-scale Brain Simulation

2.1. Brain-inspired Computing

The human brain can complete advanced computing tasks (e.g., recognition, cognition, and learning) with low frequency of neuronal spiking and extremely low power consumption. This results from highly parallel computation and event-driven schemes of computation. Energy is consumed only where and when it is required for processing information. Major challenges in imitating the human brain are replicating the time-dependent plasticity of synapses and obtaining great connectivity in neuron networks. The mix of high computing capability and density scalability can be achieved with nanodevices, by resistive-switching memory (RRAM) devices [6].

An electronic synapse with long-term and short-term plasticity is important for a brain-inspired neuromorphic system. In biological systems, long-term plasticity is the foundation of learning and memory behaviors while short-term plasticity is related to critical computational functions. The electronic synapse can vividly emulate long-term and short-term plasticity as well as voltage sensitivity in the bio-synapse, which is the key device foundation for brain-inspired neuromorphic computing [7].

Computing with high-dimensional (HD) vectors (also called hypervectors) is brain-inspired and an alternative to computing with scalars. Key features of the HD computing lie in well-defined arithmetic operations on hypervectors, scalability, fast learning, generality, robustness, and ubiquitous parallel operations. Accelerating HD computing on a parallel ultra-low power platform with optimal operations and memory accesses was presented [8].

A brain-inspired associative memory with robust retrieval and big capacity has been presented. It is named Columnar Organized Memory (COM) and consists of spiking winner-take-all (WTA) networks that are building blocks of the neocortex. A spiking WTA consists of spiking neurons linked by inhibitory connections. The message storage of a COM includes pattern storage and pattern association. The capacity of a COM was analyzed and evaluated by using simulation. It was demonstrated the capacity of a COM is linearly related to that of a spiking WTA [9].

Target classification and recognition (TCR) of high resolution remote-sensing images is important for an earth observation system and an unmanned autonomous system. A brain-inspired computing model for TCR was proposed based on deep learning and cognitive computing. An ensemble learning algorithm was developed based on deep spiking convolutional neural network and hierarchical latent Dirichlet allocation [2].

The Wisdom Web of Things (W2T) provides a social-cyber-physical space for human communication and activities. W2T generates big data during the connection of computers, humans, and things. It integrates big data related to human behaviors and brain-related big data in a social-cyber-physical space for realizing a harmonious symbiosis. Brain informatics provides the key technique of performing such an attempt through providing informatics-enabled brain study and applications in the social-cyber-physical space; therefore, creating a brain big data cycle [10].

2.2. Neuromorphic Computing Systems

Neuromorphic computing refers to various brain-inspired computers, devices, and models inspired by the interconnectivity, energy efficiency, and performance of the brain [11]. Memories are distributed in a neuromorphic approach. Adaptation and the learning mechanism in a neural system are mediated by multiple types of ‘‘plasticity’’. The most common types are homeostatic plasticity, structural plasticity, long-term potentiation, short-term plasticity mechanism, and long-term depression mechanism [12].

The activity of synapses between the pre-neuron and post-neuron is important for memory and learning. STDP is a significant learning rule in hippocampal neurons to modulate the synaptic weight (or connection strength). A memristor has been a promising candidate of artificial synaptic devices for brain-inspired neuromorphic computing. Diverse state dependent STDP functions were fulfilled with various initial resistance states. A multilevel Pt/HfOx/Ti memristor was developed as an artificial synaptic element for brain-inspired computing. Devices under various initial resistance states have diverse types of STDP and can be employed for spiking neural networks [13].

The SpiNNaker system is a multi-core computer that is developed to perform real-time simulation of the behaviors of up to a billion neurons. An IBM spiking neural network ASIC named “TrueNorth” is different from the von Neumann architecture. Synapses in the TrueNorth chip do not perform any plasticity mechanisms; therefore, they are not able to implement online learning or form memories. The aim of co-localizing computation and memory and mitigating the von Neumann bottleneck is just partly achieved. The NeuroGrid system aims to implement large-scale neural models and emulate their functions in real time. Important synapse and neuron functions (e.g., integration, thresholding, exponentiation, and temporal dynamics) are emulated directly using the physics of field-effect transistors biased in the subthreshold regime. Another method for simulating large-scale neural models is the one in the BrainScales project. BrainScales tries to fulfill a wafer-scale neural simulation platform [12].

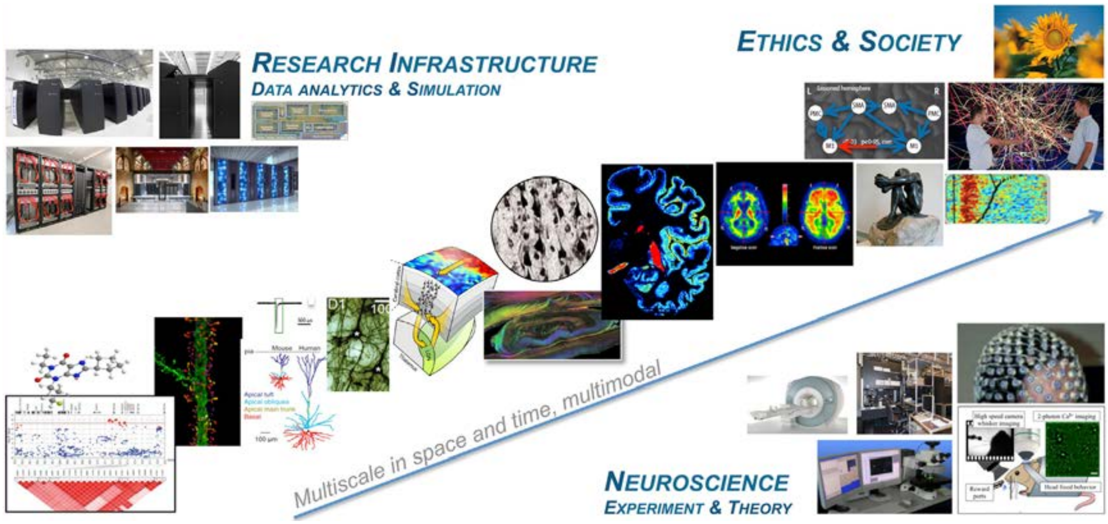

Figure 1. The Human Brain Project targets the multi-level organization of the brain [14]

2.3. Multi-scale Brain Simulation and Research

The Human Brain Project (HBP) has been launched that is a ten-year European Flagship for the reconstruction of the brain's multiscale organization. The IT architecture of the HBP is based on cloud-based collaboration platforms with workflow systems, databases, supercomputers, and petabyte storage. The HBP researches the brain at various spatial scales (from molecules to large networks) and temporal scales (from milliseconds to years) through various approaches, instruments, tools, etc. (shown in Figure 1). The HBP initially contains the following platforms: Medical Informatics, Neuroinformatics, Brain Simulation, Neuromorphic Computing, High-Performance Analytics and Supercomputing, and Neurorobotics—connected through the ''Collaboratory'' (COLLAB) interface [14].

3. Brain Association Graph and Brainnetome

3.1. Brain Association Graph

Theoretical graph methods have been employed to quantify topological attributes of complicated brain networks. Hubs with importance in the brain network can be characterized by a set of graph metrics (e.g., degree, participation coefficient, and betweenness centrality). Based on the graph metrics, network nodes can be characterized as different kinds of hubs (e.g., connector and provincial hubs) [15].

There are influences of stress on the connectivity of regional hubs in the brain; however, most of connections are integrative in nature due to their crossing distinct modules. The application of graph theory to neuroimaging data needs to reach a consensus on suitable parcellation schemes that are used in defining nodes with biological meanings, thresholding or weighting edges for computation graphs, or the reliability of graph metrics. There are still substantial gaps in the directions of research such as the careful examination of influences of stressor types and timing on adolescents' brain development and critical considerations of sex differences, prospective studies of influences of stress on adolescents and children. Metrics has been proposed that is useful for understanding influences of stress on adolescents' brains and represents a method being able to facilitate comparisons across multimodal data for developing new insights [16].

3.2. Brainnetome and the Connectome

Brainnetome is a powerful framework for exploring the brain's functional and anatomical networks at different spatiotemporal scales [22]. The connectome (the entity of neural connections in the brain) helps understand the brain with normal functions or diseases. It also helps infer how vulnerable the brain is to neurodegeneration and traumatic stress, how well the brain recovers from damages, and how intelligent a person is. Connectomics deals with the connectome as a mathematical graph with nodes (gray matter brain structures) and links of the graph (white matter tracts). The weight of the link represents the functional or structural connectivity. Graph theoretical measures can be used as biomarkers for psychiatric and neurological diseases. Diseases are often resulted from pathological alterations in specific sub-networks or individual connections. The macroscopic functional and structural connectome can be measured noninvasively. Functional brain connectivity can be given as correlation values between traces of electrical activity in various brain areas. Structural connectivity can be measured by diffusion tensor imaging (DTI). It is necessary to integrate connectivity measurements from various modalities for a compressive picture of the macroscopic connectome [17].

Mapping brain imaging data to networks, where nodes indicate anatomical regions of the brain and edges represent the occurrence of fiber tracts between them, has been able to perform a graph-theoretic analysis of the human connectome. It has been revealed that the connectome has a hyperbolic geometry and a complicated structure on the scale between edges and mesoscopic anatomical communities within cerebral hemispheres. This structure with simplicial complexes of various sizes and cycles describes the higher-order connectivity among various regions of the brain [18].

The connectome deals with wiring patterns of the neurons in the brain. The influence of its constituents on the dynamics is a critical topic in systems neuroscience. The key role of specific structural links between neuronal populations for the global stability of cortex was investigated and the relationship between experimentally observed activity and anatomical structure was elucidated. A framework was proposed that can evaluate the rapidly growing body of connectivity data based on basic constraints on brain activity and combine physiological and anatomical data to create a consistent picture of cortical networks [19].

4. Brain Imaging

Brain imaging and relevant data from other sources can be useful in predicting "brain age" (an individual's apparent age) after comparing the individual's data with a population dataset spanning a range of ages. The difference between the actual age (the "delta") and the brain age can be calculated, which provides a result regarding whether a brain has aged [20].

Table 1. Some Methods of Brain Imaging and Findings in DOC

Methods	Usages	Findings in DOC
Electroencephalography (EEG)	Records electrical activities and explores neural oscillations/ interactions or potential fluctuations time.	1. Several indexes of functional brain networks in delta and alpha bands indicate correlations with the consciousness level. 2. Enhanced delta power and reduced theta and alpha power in the DOC. 3. Mismatch negativity, P3, etc. provide the information of the consciousness level.
Positron Emission Tomography (PET)	Detects local metabolic processes or the changes of blood flow in the brain in a task or resting state.	1. Frontoparietal networks and their connections to thalamus nuclei are significant for the occurrence of consciousness. 2. Global brain metabolism cannot be a sensitive marker for tracing the consciousness level.
Functional Magnetic Resonance Imaging (fMRI)	Detects brain activity through measuring blood-oxygen-level-dependent changes and explores functional connections between brain areas.	1. Functional connections in the default mode network (DMN) and between the DMN and executive control network can be the key for the DOC prognosis/diagnosis. 2. A number of resting state networks are disrupted in the DOC.
Diffusion Magnetic Resonance Imaging (dMRI)	Measures the diffusion of water along axon, estimates major fiber tracts between brain areas.	1. Fibers that connect cortical regions within the DMN and between DMN regions and thalamus are correlated to consciousness levels. 2. DOCs with various etiologies reveal different distributions of impaired white matters.
Functional Near-infrared Spectroscopy (fNIRS)	Detects brain activity according to the attenuation changes of near infrared through one's cortex, explores functional connections.	fNIRS has a unique value for quantifying the brain network activity and therapeutic effects in the DOC.

Imaging methods such as X-ray computed tomography and electroencephalography (EEG) have been employed in understanding nervous systems and clinical services, but their spatial resolution is limited and has weak relevance with the cellular activity of the neuron network. Microelectrode arrays can be used on the cortex surface or implanted into the deep brain, monitoring neuronal activities through capturing intracellular and extracellular signals. A mathematical model was created to study the optical performance of an implantable and thin-film image sensor for investigating neuronal fluorescence activities in the deep brain. Such a simplified model based on the photon transport theory achieves an accuracy comparable with the standard Monte Carlo ray tracing method [21].

As for the functional networks in the brain, functional neuroimaging enables to measure the brain's electrical activity, hemodynamic activity, and metabolic activity. These activities help measure impaired brain networks of patients with disorders of consciousness (DOC). As for the anatomical networks in the brain, diffusion MRI is a non-invasive technology to show the micro-geometry of nervous tissues and exploring the connectivity of white-matter fibers. Table 1 shows some methods of brain imaging and findings in DOC [22].

5. Brain-inspired Chips and Brain-inspired Devices

Neuromorphic computing refers to the hardware acceleration of brain-inspired computing. It uses the VLSI (very-large-scale integration) system with electronic analog circuits to emulate the neuro-biological architecture of the nervous system. How to improve the power efficiency and reduce the power consumption of neuromorphic computing systems (NCS) is a key issue. One way is using neuromorphic-specific hardware, e.g., neuromorphic chips and emerging nonvolatile memory in neuromorphic computing. In addition, optimizing hardware-aware algorithms also saves energy and improves the performance of emerging devices. Massive parallelism with "spikes" (the short pulses that carry information between neurons) is the future of the NCS design. Digitalized NCS and spike based NCS will be developed fast [23].

Memristors are nanoscale devices that have been proposed for use as synapses in a brain-inspired computing system. A synapse structure that can perform both an inhibitory and an excitatory action has been presented. This structure has the exponential-like learning behavior. Users can control learning behaviors and remedy effects of switching rate mismatch in memristors through discretizing the neuron spike in time. Synapses can be employed to fulfill spiking neural networks with STDP based on-chip learning [24].

The fast growth of brain-inspired computing along with the inefficiencies in the CMOS realization of neuromorphic systems has resulted in the development of efficient hardware realization of functional units of the brain (i.e., neurons and synapses). But much work has been done in the electrical area with possible limitations in interconnect losses, switching speed, and the packing density of large integrated systems. Therefore, neuromorphic engineering in the photonic area has obtained much attention. A purely photonic operation of an Integrate-and-Fire Spiking neuron has been proposed, which relieves the energy constraints of phase change materials (PCM) [25].

6. Brain-Computer Interface, Brain-Inspired Robotics, and Cyborg

Brain-computer interfaces (BCIs) translate electrical signals from brain activity into interpretable information without neuromuscular control, reflecting a user's ideas and intents. The BCI technology could be divided into invasive and non-invasive according to whether a surgery is conducted. In non-invasive BCIs, the EEG-based BCI speller has been used for paralyzed patients because of low cost, a high time-resolution, external electrode safety, and extensive applications [26].

Brain-machine interface (BMI) is an emerging technology that contributes to the development of artificial limbs and new input devices by integrating advanced technologies (e.g., signal analysis, wireless communication, robot control, and neural electrodes). Neural electrodes are a key component of the BMI because they can record many rapid signals emitted by neurons. Electrodes are designed according to various templates using diverse materials to obtain accurate consistent, and stable signals. Micromachining technologies and microelectromechanical systems (MEMS) can reduce the of electrode size. Various designs and materials are available to record many selective and low-noise signals. Neuronal signals have been divided into three categories: non-penetrating type—records signals from on or beneath the scalp; penetrating-type electrode—measures signals in vivo, particularly in the brain; and microelectrode array (MEA) electrode— records neuronal signals in vitro [27].

Table 2. Platforms for Robot Control Based on SNN [28]

Platform Names	Methods
Musculoskeletal Robots	Integrating Myorobotics with SpiNNaker the proof of principle of a system.
Neurorobotics Platform	Design, import, and simulate various robot bodies and diverse brain models in a rich environment.
Retina Simulation	The platform is integrated in the Neurorobotics Platform (NRP).
AnimatLab	Provide functions (e.g., robot modeling), two neural models, and plugins used for importing other models.
iSpike	Interface between the iCub humanoid robot and SNN simulators
Neural Self-driving Vehicle Simulation Framework	A visual encoder from camera images to spikes inspired by the silicon retina, and a steering-wheel decoder.

Spiking-neural-networks (SNNs) computation greatly benefit from parallel computation. A spiking neuron does not need to receive weight values from each presynaptic neuron at each computation step. Only a few neurons are active in an SNN at each time step, the classic bottleneck of message passing is removed. Communication time and computation cost are more well-balanced in SNN parallel operation compared with traditional ANNs. By mimicking the brain mechanism, SNNs have demonstrated great potential in gaining sophisticated robotic intelligence according to computation capabilities, speed, and energy efficiency. Some available platforms are listed in Table 2. A big challenge of control tasks based on SNNs is a lack of a commonly applicable training method like backpropagation in traditional ANNs [28].

Cognitive developmental robotics (CDR) deals with robots that can interact with a dynamic environment and have brain-inspired cognitive abilities, e.g., memory and learning. CDR can respond to a dynamic environment through a SNNs-based controller. In order to develop neuro-robots, it is necessary that emotional cognition makes robots with anthropomorphic and diversified emotions have natural communication with humans and environment. Brain-inspired intelligent robots can be products with the intersectional development of neuroscience and robotics [29].

The mix of artificial microrobots and natural organisms (called cyborg microrobots) has paved a hopeful way for future development of microrobots, especially for their applications in biomedicine. A cybernetic organism (cyborg) is an organism that has restored functions or enhanced abilities because of the combination of artificial components and technologies. Applications of cyborg microrobots include water purification, cancer therapy, targeted drug delivery, etc. Microrobots used for targeted drug delivery can control the time and location of the drug release to increase the efficacy as well as decrease the drug side effect [30].

The efficiency of a quantum robot over a classical robot was addressed, using an architecture for quantum robots based on three fundamental parts: sensory units, a quantum controller/actuator, and multi quantum computing units. Quantum robots can be artificially intelligent measurement systems that are able to measure target quantum systems and act on targets based on measured results; therefore, they can be used to manage quantum physical systems, leading to an adaptive dynamics and fast optimization of target quantum systems. A connection between nanotechnology, quantum robotics, and quantum Artificial Life (ALife) research was created. This is especially relevant to the development of quantum cyber-physical-cognitive (CPC) systems within the context of quantum nanotechnology, including the possibility of interaction and nanoscale management of quantum systems. More recent works focused on quantum robotics and machine learning [31].

The development of neural implants for enhancing people's memory enables to develop cyborgs (human-machine hybrids) with superior capacities. Individuals' ethical assessments of memory implants indicates differences in their intentions to use them, but does not moderate the influence of negative emotions, positive emotions, effort expectancy, performance expectancy, and social influence on the intention of using them [32].

7. Conclusion

Brain-inspired computing enhances the efficiency of information processing and computation and save energy greatly because it is based on computing units with the co-location of memory and processing. This is very important for achieving strong AI, especially for Big Data analytics. Neuromorphic chips help improve the power efficiency and reduce the power consumption of neuromorphic computing systems. Also, optimizing the hardware-aware algorithm saves energy and improves the device performance.

Brain association graphs based on graph theories quantify topological structures and attributes of complex brain networks. Brainnetome has been a key tool for studying the brain in normal functioning and disease. Brain association graphs, brainnetome, and neuroimage processing play important roles in studying the structure–function interactions of the brain.

Brain-computer interfaces enable to translate electrical signals from brain activities into interpretable information and brain-machine interfaces help develop artificial limbs and new input devices. Spiking-neural-networks have great potential in gaining sophisticated robotic intelligence. Quantum robots can measure target quantum systems and manage quantum physical systems. The development of neural implants for enhancing people's memory helps develop powerful cyborgs.

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