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Review

Progress and Challenges of Neuroscience and Brain-inspired Artificial Intelligence

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Abstract: Neuroscience and brain-inspired artificial intelligence are significant research areas. Many countries have launched brain-related projects in which neuroscience and brain-inspired artificial intelligence are major targeted areas to increase national interests and enhance their strength in key areas such as military and homeland security in the competitive global world. Methods, emerging technologies, and progress in neuroscience and brain-inspired artificial intelligence are introduced in this paper that specifically include brain-inspired computing, brain association graph, brain networks, the connectome, brain reconstruction, imaging technologies used for the brain, chips and devices inspired by the human brain, brain-computer interface or brain-machine interfaces, cyborg, neuro-robotics, and quantum robotics. Challenges in some of the topics are also presented and discussed.

Keywords: Brain-Inspired Computing, Brain-Inspired Artificial Intelligence, Neuroscience, Connectome, Brain Imaging, Brain-Computer Interface, Cyborg, Neuro-Robotics

Introduction

Biological neurons and synapses work well through processing and storing information simultaneously, while maintaining adaptability. Massive computation is fulfilled with extremely low energy consumption due to the plasticity and the co-location of memory and computing that are unique to the human brain. Biomimetic soft materials were used for synaptic connections. A synaptic device has memristive attributes that emulate biological synaptic plasticity. Neuromorphic computing deals with various computers, devices, and models inspired by the interconnectivity, performance, and energy efficiency of the human brain. Architectures for neuromorphic computing are designed to emulate the adaptability and energy efficiency of the brain (Hasan *et al.*, 2018).

Artificial Spiking Neural Networks (SNNs) try to emulate brain features (e.g., event-triggered processing, spike-based data encoding, and temporal processing of data) to fulfill energy-saving learning networks. The potential of SNNs for ubiquitous Internet of Things (IoT) and other applications can be fulfilled only if energy-efficient and dedicated parallel hardware solutions are developed (Nandakumar *et al.*, 2018). Wireless Electroencephalography (EEG) sensors, edge devices, cloud-assisted data capture, and longitudinal brain monitoring and alerting were used in brain science and technology (Nick *et al.*, 2015). Cognitive processes about network interactions during creative performance have been identified and they are: Internally focused attention, prepotent-response inhibition, and goal-directed memory retrieval. Correlational research using prediction modeling shows that functional connectivity between networks enables to predict an individual's ability in creative thinking (Beaty *et al.*, 2019).

How the features of the online world influence human's attentional capacity, memory process, and social cognition was studied. It was demonstrated that the Internet could lead to alterations in human's cognition that may be reflected in some changes in the brain. Specifically, the influences on the brain and cognitive process lie in: (1) Rapid and ubiquitous access to online information outcompeting previous transactive systems and potential internal memory processes; (2) multi-faceted incoming information streams making people be involved in attentional-switching and "multi-tasking"; and (3) the online social world making it possible that properties of social media have influences on life (Firth *et al.*, 2019).

The purpose of this paper is to introduce methods, emerging technologies, and progress in neuroscience

and brain-inspired artificial intelligence, and present and discuss challenges of some topics. Brain diseases are not the focus in the paper. The rest of the paper is arranged as follows: Section 2 introduces brain-inspired computing; Section 3 presents brain association graph, brain networks, the connectome, and brain reconstruction; Section 4 describes imaging technologies used for the brain; Section 5 presents brain-inspired chips and devices; Section 6 deals with brain-computer interface or brain-machine interfaces, cyborg, neuro-robotics and quantum robotics; and Section 7 is the conclusion.

Brain-Inspired Computing

Neuromorphic systems (low-energy consumption) have gained great attention, spurring forward the development of brain-inspired hardware systems that operate on principles different from conventional computers and therefore consume much less power (Diehl *et al.*, 2016). Table 1 shows a comparison between the computer and the human brain (Otoom, 2016). The abbreviations in the table are as follows: MISD—multiple instructions and single data; SIMD—single instruction and multiple data; MIMD—multiple instructions and multiple data; STM—short-term memory; LTM—long-term memory; and MM—main memory.

A train-and-constrain method was present that enables the mapping of machine learned (Elman) RNNs (recurrent neural networks) on a substrate of spiking neurons, while being compatible with current neuromorphic systems. The method consists of first training RNNs using backpropagation, then discretizing weights and ultimately converting them to spiking RNNs (Diehl *et al.*, 2016). Brain-inspired hyperdimensional (HD) computing emulates cognition tasks by computing with hypervectors. MHD, a multi-encoder hierarchical classifier was proposed, which enables HD to take full advantages of multiple encoders without increasing the cost of classification (Imani *et al.*, 2018).

The concept of Universal Memcomputing Machines (UMMs) was introduce. UMMs are brain-inspired computing machines, thus processing and storing information on the same location. Memory properties of UMMs give them intrinsic parallelism, information overhead, universal computation power, and functional polymorphism (Traversa and Di Ventra, 2015). Brain-inspired mechanisms such as spike timing dependent plasticity (STDP) enable agile and fast on-the-fly adaptability in the SNNs. When incorporating nanoscale resistive non-volatile memory components (high-density integration capability and extremely low energy consumption), a hardware with SNNs will have several orders of reduction in energy consumption. A dendritic-inspired processing architecture was presented in addition to complementary metal-oxide semiconductor (CMOS) neuron circuits (Wu and Saxena, 2018).

Table 1: A computer-brain comparison

Aspects	Computer	The human brain
Size	Big	Compact
Software	Programs	Minds
Hardware	Parallel (not long time ago)	Massively parallel
Software/hardware	Separate	Brain emerged from minds
Speed	Faster	Slower (most situations)
State	Digital	Analogue
Assembly	Man-made	Self (reconfigurable)
Information unit	Bit	Symbol
Power	High	Extremely low
Circuit	Silicon	Neuronal
Storage	Memory (modular)	Synapses
Dimensionality	Single	Multi
Basic computing element	Processor/functional unit	Neuron (or Cortex)
Information representation	Digital	Mixed
Processing	Serial (most computers), parallel	Parallel
Clocking/firing	Synchronous (time driven)	Asynchronous (event driven)
Number of connections	Limited (in general)	Huge
Communication	Bidirectional	Unidirectional
Metrics	Time and throughput	Time and quality
Memory hierarchy	L1, L2, … MM, hard drive, …	STM, LTM, EM, sensory, …
Information transmission	Electrical	Electro-chemical
Memory addressing	Byte addressable	Content addressable
Parts	Reliable	Noisy
Information encoding	Bits	Rates or Times
Clock shape	Regular periods	Spikes (event driven)
Architecture	SISD, SIMD, MIMD	MISD
Number of processing elements	Hundreds of processing elements	10^{11} neurons, each receiving and giving about 10^4 synapses

Brain-inspired circuit design is thwarted by two limits: (1) understanding the event-driven spike processing of the human brain and (2) developing predictive models for the design and optimization of cognitive circuits. A model for SNNs based on STDP in Resistive Switching Memory (RRAM) synapses was presented. Both an analytical model and a Monte Carlo (MC) model were presented to explain experimental data from a neuromorphic hardware. It was shown that the MC model of RRAM circuits and the analytical compact model of the STDP dynamics accurately predicted the learning behaviors in a spiking network with RRAM synapses (Pedretti *et al.*, 2017).

Brain-inspired computing is based on neural morphological engineering. TensorFlow was developed by the Google brain. It has been a frequently used neural network simulation framework. TensorFlow implements neural networks using Dataflow Graphs (DFG). It enables the DFG to partition into several subgraphs and use them simultaneously on multiple CPUs and GPUs. In general, brain High-Performance Computing (HPC) platforms suffer from poor scalability, a slow speed, and too much energy consumption. The Codelet model was proposed based on the advancement of the dataflow model. It successfully fulfilled distributed computation on a heterogeneous system and effectively improved the computation capability and speed due to a fine-grained asynchronous program execution and resource allocation. A brain-inspired computing platform was proposed based on the Codelet model, which fine-grained multithread scheduling policy and the asynchronous execution plan was implemented (Zeng *et al.*, 2019).

Brain Association Graph, Brain Networks, the Connectome, and Brain Reconstruction

Graph theory is very useful for neuroscience research and it is a challenge to understand how topological architecture and functional features are related in the brain. However, research on task-based functional neuroimaging has uncovered a core set of brain regions such as parietal and frontal lobes that support various cognitive tasks. A graph measure for describing the functional diversity of brain regions was proposed. The graph method has potential for studying how the functional diversity of brain regions evolve during brain development or is disrupted due to neuropsychiatric disorders (Yin *et al.*, 2019).

Complex network theory has been successfully used in discovering the brain topology and showing alterations to the brain network structure due to brain diseases, behaviors, and cognitive functions. Functional connectivity networks represent various brain regions as the nodes and the connectivity between them as edges of a graph (Munia and Aviyente, 2019). The relationship between ages over the adult lifespan and the functional connectivity within the large-scale brain networks was investigated. Graph analysis indicated that there was widespread reorganization of the functional brain networks while the age increased and that the reorganization proceeded towards a more integrated network topology. It was shown that there were substantial alterations in functional connectivity patterns that were characterized by higher between-network connectivity and weaker within-network connectivity in increased ages (Bagarinao *et al.*, 2019).

The connectome deals with neuron wiring patterns in the brain. The key role of specific structural links between neuronal populations for the global stability of cortex was investigated; the relation between experimentally observed activity and anatomical structure was explained (Schuecker *et al.*, 2017). The connectome prediction method has been used to evaluate the ability of creative thinking from the patterns of brain connectivity at rest and during tasks, indicating that the variation in brain-network connectivity presents a trustworthy biomarker of the ability in creative thinking (Beaty *et al.*, 2019). A connectome-based hybrid model for the brain network was developed from diffusion-weighted Magnetic Resonance Imaging (MRI) tractography and region parcellations from anatomical MRI. It integrated individual functional and structural data with neural population dynamics to help multi-scale neurophysiological inference (Schirner *et al.*, 2018).

An entire brain is usually sectioned into many slices for high resolution imaging. Brain-related research in anatomical labeling, visualization, and 3D measurement can benefit from reconstructed 3D virtual brains. With the 3D reconstruction of brain volumes, a 2D cross-section view from any angles is feasible, thus leading to more accurate anatomy labeling. Two methods for structure correction were presented for the brain reconstruction with multilayer tissue sections and they are: Tissue flattening and structure-based intensity propagation. Tissue flattening improves the quality of a reconstructed brain (Liang *et al.*, 2018).

Imaging Technologies Used for the Brain

There are major structural and functional changes in the brain during the first decade of life, which lays the foundation for human cognition. But a non-invasive imaging technology used to study brain functions throughout neurodevelopment is limited because of the growth in head-size with the age and much head movement in young users. The development of quantum science and technology has allowed the development of wearable magnetoencephalography (MEG) technology that is likely to revolutionize electrophysiological measurements of brain activity. A lifespan-compliant

system of MEG was demonstrated, which showed a new approach to functional imaging (Hill *et al.*, 2019).

Brain imaging with MRI and computerized tomography enables to find biomarkers of brain pathology that are significant for the accurate diagnosis and phenotyping of various neurological diseases. Reading brain imaging text reports would be helpful for research as well as clinical practice. A natural language processing algorithm for identifying brain imaging phenotypes was developed. Using radiologists' reports of brain imaging in clinical practices should be helpful for the cohort development and outcome ascertainment of neurological phenotypes (Wheater *et al.*, 2019).

Imaging neural activities at the cellular level in the deep brain is necessary to understand structures and functions of nervous systems. Completely implantable optical sensors that were recently developed enable to capture fluorescence signals. A simplified model for studying the photon transport in the biological tissue was developed and it was used to understand the optical performance of an implantable fluorescence imager. Spatial resolution of the implanted imager was computed and imaging qualities for groups of neurons in 2D and 3D configurations were assessed (Nazempour *et al*., 2019).

Electrical impedance tomography (EIT) has been regarded as a promising candidate for brain stroke imaging because of its compactness and potential applications in bedside and emergency settings. The electrode–skin contact impedance and the low conductivity of skulls bring practice challenges to the EIT head imaging. The applications of capacitively coupled electrical impedance tomography (CCEIT) in brain imaging were investigated. CCEIT is a new contactless EIT technology that uses voltage excitation (Jiang and Soleimani, 2019).

Chips and Devices Inspired by the Human Brain

There are two main methods to develop Artificial General Intelligence (AGI): Neuroscience-oriented and computer-science-oriented. The Tianjic chip was developed that integrates the two method to present a synergistic and hybrid platform. It has reconfigurable building blocks, a many-core architecture, and a streamlined dataflow. It accommodates computer-science-oriented algorithms for machine learning and implements several coding schemes and brain-inspired circuits easily (Pei *et al.*, 2019).

Many efforts have been made to create artificial synapses and neurons using different solid-state systems with ferroelectric materials, oxide-based memristive materials, phase-change materials, etc. Brain-inspired hardware paves a potential pathway to fulfill complicated cognitive tasks with low energy consumption. Using artificial synapses comprising solid-state devices with nonvolatile and analog-memory functions is attractive for the realization of low-power, high-performance, and adaptive artificial neural networks (ANN). The artificial spintronic synapse enables to learn patterns and execute operations of brain-like associative memory. Spintronics devices generally permit high-speed and virtually unlimited read/write operations and information storage without using a power supply, keeping promise for the fulfillment adaptive neuromorphic hardware with low power consumption (Fukami and Ohno, 2018).

Memory plays a significant role in computing and Phase-Change Memory (PCM) is a very innovative emerging technology of non-volatile memory. A key feature of brain-inspired computing is the co-location of processing and memory. It is also inspired by using PCM components and people can design a co-processor with multiple crossbar arrays of PCM to facilitate training deep neural networks. It is very promising to implement in-place computing with data saved in a PCM device (Sebastian *et al.*, 2018).

STDP and a neuroscience-inspired model of learning were used in a bioinspired approach to programming memory devices. This approach was adapted to various memory devices that include stochastic binary memories such as conductive bridge memory and multivalued memories (e.g., phase-change memory). Emerging nonvolatile memory devices such as memristor are very compact and can be embedded in the CMOS circuitry, offering the benefit of nonvolatility and the advantage of fusing memory and computation. Long-term memory is stored in synapses (connections between the neurons) that are active computation units in the human brain. A synapse can transmit information from one neuron to another as well as adjust its strength (synaptic weight). This adaptation (called synaptic plasticity) is regarded as a very significant phenomenon for long-term learning. A cognitive system can have an instant on/off and provide the possibility of extremely reduced power consumption for the IoT (Querlioz *et al.*, 2015).

Brain-inspired hardware systems have obtained much traction due to low power consumption. Its asynchronous and distributed feature of neural computation due to low-energy spikes leads to massive parallelism and high energy efficiency. The large-scale neuromorphic hardware enables the low-power implementation of large-scale neural networks used for a real-time applications. The IBM TrueNorth Neurosynaptic System is such a platform. It has close to state-of-the-art properties in different tasks of pattern recognition with extremely high energy efficiency due to the operation in the spiking domain. A spike-based realization of Long Short-Term Memory (LSTM) on the IBM TrueNorth Neurosynaptic Processor was developed. A standard

LSTM was split into modules and separately approximated using spiking neurons. The modules were in the form of corelets that were combined/connected and mapped to shape spike-based LSTM networks (Shrestha *et al.*, 2017).

Brain-Computer Interface, Cyborg, Neuro-robotics, and Quantum Robotics

Brain-Computer Interface

A Brain-Computer Interface (BCI)-based system can perform capturing, amplifying, digitalizing, processing and decoding signals that are generated from a user while imagining movement, dealing with decision-making and finishing a cognitive task. A BCI device can be a tool for cognitive rehabilitation, bring many benefits for patients in various aspects such as visuospatial orientation, Short-Term Memory (STM), and attention. In addition, a BCI system can serve as a safe place (for example, using the virtual reality technology) to perform rehabilitation training, reducing health risks for patients. A BCI system was demonstrated to generate important modulations in some brain wave characteristics that promote changes in cortical organization and connectivity. A BCI system assists in cortical reorganization and cognitive skill recovery. But the BCI needs to adapt to a user's cognitive profiles according to mental state classification, signal processing, and feedback provision (da Silva-Sauer *et al.*, 2019).

An architecture of brain-inspired SNNs was developed that enables to learn and reveal deep in time–space structural and functional patterns from spatiotemporal data. The patterns can be expressed as deep knowledge in a partial case using deep spatio-temporal rules. This is a trend for developing a new type of brain-computer interface that is called Brain-Inspired Brain–Computer Interface (BI-BCI). A BI-BCI was developed and it could extract neural trajectories. Deep spatiotemporal rules on structural and functional interactions of distinct brain areas were employed for the event prediction in the BI-BCI (Kumarasinghe *et al.*, 2020).

A brain-computer interface (BCI) tries to make people interact with the external world via an alternative and non-muscular communication channel that utilizes brain signal responses to finish cognitive tasks (Baek *et al.*, 2019). An Electroencephalography (EEG)-based BCI, especially a BCI using Motor-Imagery (MI) data, has the potential in clinical applications. MI data are generated when a user imagines the limb movement (Padfield *et al.*, 2019). However, major challenges affecting the widespread implementation of the BCI are outlined in Table 2.

Table 2: Major challenges of the BCI wide applications (Baek *et al.*, 2019; Padfield *et al.*, 2019)

Aspects	Challenge description
Flawed Testing Processes	Extensive testing on wide and large populations is needed to achieve improvement; however, testing processes in themselves are sometimes flawed.
Ethical Issues	Ethical standards are required to guide the development of the BCI, including suitable utilization of bio-signal data, privacy, and liability if accidents happening in using controlled apparatus.
Problems encountered during the BCI Use	BCI illiteracy is a barrier to the widespread implementation (especially for EEG-based interfaces). It sometimes happens when users cannot control a BCI since they do not produce required brain signals with a high quality.
Commercialization	1) Adapting lab-based technology for a wider world with the consideration of costs, general appeal, reliability and usability, choice of technology, and intuitivism. 2) Major developments are demanded in user-friendliness, sensors, and overall system performance for the non-invasive BCI; completely implantable systems are required for the invasive BCI to improve the system performance and robustness and clinical trials are necessary to guarantee the system safety.
Research and Development	1) Design of dependable systems with steady performance for diverse users (various mental states) in various environments. 2) In interface paradigm design, control commands (e.g., moving a cursor) in the current BCI system are assigned to specific mental states. A user must implement a specific mental task for encoding a desired control command. But requirements for a visual stimulus (e.g., letters and flashing digits) that the user needs to watch has limited the accessibility, flexibility, and usability of the BCI. 3) Troubles with signal processing challenges (especially for MI EEG), including feature extraction/selection (due to the non-stationary, highly non-linear, and artefact-prone property of EEG data) and data fusion (especially a combination of data from various EEG channels) for data dimensionality reduction and the improvement of classification results. 4) In brain activity monitoring, different neural signals have been used for the BCI. EEG is very frequently employed since it is noninvasive. But the requirement for wet electrodes limits the daily use of the BCIs.

A future BCI system should (1) be easy to install; (2) work well in all scheduled environments; (3) be convenient, comfortable, and provide aesthetically acceptable mountings; (4) operate by telemetry without requiring wiring; (5) have functions for many hours without any maintenance; and (6) interface easily with diverse applications (Baek *et al.*, 2019).

Cognitive Knowledge Base (CKB) is a core of cognitive knowledge learning for cognitive robotics and Machine Learning (ML) systems as well as Brain-Machine Interfaces (BMI). Features of the semantical CKB are quantitative, relational, weighted, hierarchical, and nonnegative. Autonomous knowledge acquisition and comprehension are key for BMI and interactions. A method for autonomous generation of the CKB by cognitive machines was presented based on models of cognitive machine learning and concept algebra. An algorithm of CKB generation was developed for autonomous machine learning from semantic expression and human's knowledge (Wang *et al.*, 2017).

Cyborg and Robotics

A Neuro-Robotics System (NRS) is the "brain" of a neuro-robot. Generally, a neuro-robot should have the following features and functions: (1) A human-like brain; (2) fusing multi-sensory information and modeling/simulating a complex environment; (3) emotion expression and interacting with humans naturally; (4) synergy, redundancy, and intelligence in brain-like control; 5) brain-like cognition and self-learning; and 6) a bio-inspired body for flexibility and adaptability (Li *et al.*, 2019). The framework of an NRS is illustrated in Fig. 1.

Cyborg is a human-machine hybrid and has been an emerging technology that helps the disabled patients restore limb functions as well as enables healthy people to obtain superpower. Cyborg microrobots have started emerging and a macrophage-based microrobot for active targeted cancer therapy has been proposed (Wei *et al.*, 2019). Figure 2 illustrates the fabrication process of the microrobot (left) and targeted tumor cell destruction and therapy process (right).

The quantum science and technology infrastructure in the future requires the development of quantum Cyber-Physical-Cognitive (CPC) systems, integrating quantum communication and quantum information technology, quantum Artificial Intelligence (AI), and quantum robotics. Quantum robotics deals with the following main points (Gonçalves, 2019):

- Field-based cognitive science is required to effectively deal with the computational basis for quantum AI
- Entanglement is the key dynamics for the computation of quantum CPC systems
- Quantum CPC systems are not closed and interactions with the environment are a key feature of the systems
- AI needs to be integrated in quantum CPC systems so that computation needs the entanglement as well as takes advantage of the entanglement for bring adaptive changes in the environment

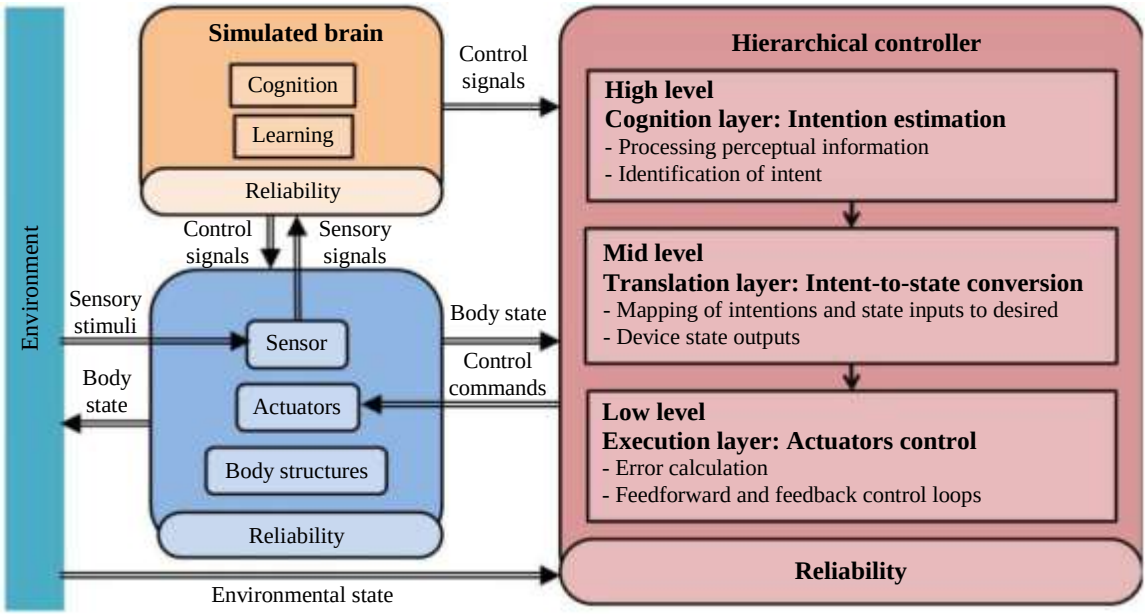

Fig. 1: An NRS framework (Tucker *et al.*, 2015; Li *et al.*, 2019)

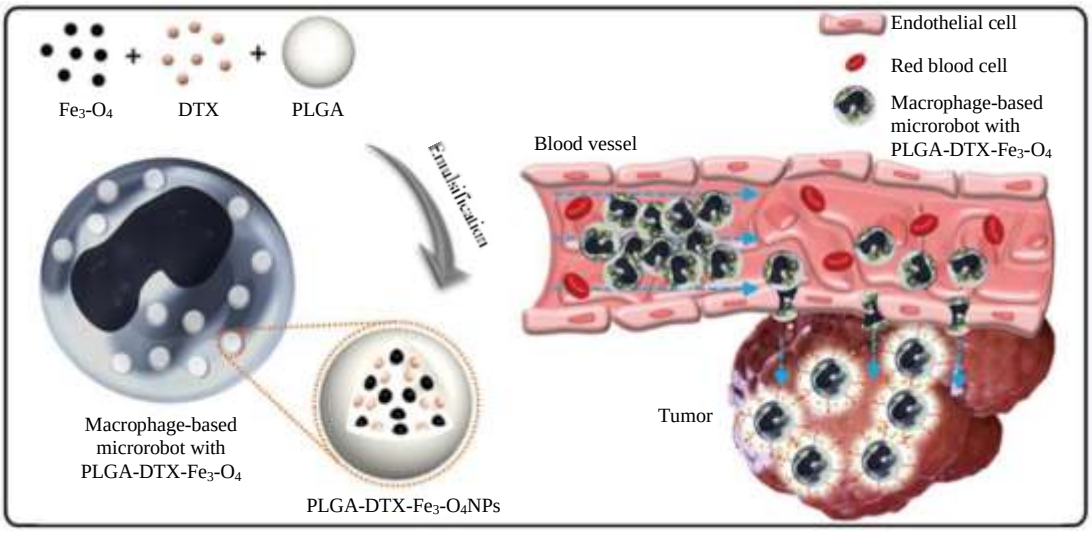

Fig. 2: A microrobot used for cancer therapy (Han *et al.*, 2016) copyright 2016, springer nature

Conclusion

Brain-inspired computing is based on neural morphological principles. Its key features are the co-location of processing and memory, high efficiency, and ultra-low energy consumption. Also, it is inspired by using PCM and promising in fulfilling in-place computation with data saved in a PCM device.

The brain association graph method has potential for examining the functional diversity of specific brain lobes. Complicated network theory has been used in studying the brain topology. The connectome discloses neuron wiring patterns in the brain. It has been used to assess an individual's ability in creative thinking from the patterns of brain connectivity. Reconstructed 3D virtual brains enable to benefit brain-related research and development. Brain imaging helps understand structures and functions of the nervous system.

A BCI device can be a tool for cognitive rehabilitation. Also, a BCI system can be used in rehabilitation training, reducing health risks for patients. Main challenges of the BCI lie in flawed testing processes, ethical issues, problems encountered during the BCI use, commercialization, research and development. Cyborg technology can help disabled patients restore limb functions and enable healthy people to obtain superpower. A microrobot can be used in cancer therapy. The quantum infrastructure in the future requires that the quantum CPC system integrate quantum communication and quantum IT, quantum AI, and quantum robotics.

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Author's Contributions

Both authors contributed equally to this paper.

Ethics

In this article, ethical principles related to scientific research articles are observed. The corresponding author confirms that both authors have read, revised, and approved the paper.

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