

Imitating the Brain with Neurocomputer

A “New” Way Towards Artificial General Intelligence

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Abstract: To achieve the artificial general intelligence (AGI), imitate the intelligence? or imitate the brain? This is the question! Most artificial intelligence (AI) approaches set the understanding of the intelligence principle as their premise. This may be correct to implement specific intelligence such as computing, symbolic logic, or what the AlphaGo could do. However, this is not correct for AGI, because to understand the principle of the brain intelligence is one of the most difficult challenges for our human beings. It is not wise to set such a question as the premise of the AGI mission. To achieve AGI, a practical approach is to build the so-called neurocomputer, which could be trained to produce autonomous intelligence and AGI. A neurocomputer imitates the biological neural network with neuromorphic devices which emulate the bio-neurons, synapses and other essential neural components. The neurocomputer could perceive the environment via sensors and interact with other entities via a physical body. The philosophy under the “new” approach, so-called as imitationalism in this paper, is the engineering methodology which has been practiced for thousands of years, and for many cases, such as the invention of the first airplane, succeeded. This paper compares the neurocomputer with the conventional computer. The major progress about neurocomputer is also reviewed.

Keywords: Artificial general intelligence (AGI), neuromorphic computing, neurocomputer, brain-like intelligence, imitationalism.

1 Introduction

For a long time, making intelligent machines has been a big dream of our human beings. From the early days of the conventional computer, it is regarded as a such platform. For example, the proposal for the Dartmouth summer meeting on artificial intelligence (AI) in 1956 claimed that^[1] “as the speeds and memory capacities of present computers may be insufficient to simulate many of the higher functions of the human brain, but the major obstacle is not lack of machine capacity, but our inability to write programs taking full advantage of what we have.”

During the past six decades, there are roughly four methodologies to achieve some kinds of AI: symbolism, connectionism, behaviorism and statisticalism. These four methodologies had epoch-making achievements in AI by seizing some characteristics of the intelligence from different perspectives. In recent years, deep learning is surging around the world, especially significantly succeeds in image and voice recognition, pushing AI forward into the third revolution.

In particular, AlphaGo, which combines the ideas of deep learning (connectionism), feature matching and linear regression (statisticalism), Monte Carlo search (symbolism) and reinforcement learning (behaviorism), and utilizes the high performance computing (CPU+GPU) and big data

(160 thousand human games and 30 million self-playing games), successfully defeated top Go player Lee Sedol in March 2016, and has recently ranked the world’s first occupation of professional Go. The rapid progress of AI has attracted global attention: Countries are launching their policies or plans to encourage the AI related research, investment on AI has soared. The ethical problems relating to the fact, such as intelligent robots will overtake the intelligence of human and even destroy the human being, once again becomes a hot topic on media and are now being seriously concerned and studied by the academic communities.

The machine intelligence that could successfully perform any intellectual task that a human being can, be adaptive to the external environment, and even forms its own self-awareness, is termed as artificial general intelligence (AGI), full AI or strong AI. Till now, the artificial intelligence systems could only realize specific functions or given functions, and cannot adapt to complex environments or constantly develop new functions as human does. Therefore, these AI systems are still domain-specific AI, weak AI or narrow AI.

Could the strong AI be made successfully by use of the four classic methodologies or the combination of them? It is still disputable among the researchers but most of them hold a negative viewpoint that, even with higher performance computing platforms and much more big data, such AI only can progress quantitatively rather than qualitatively. The underlying reason of this viewpoint is that it is impossible to produce strong AI before we really understand the principles of our intelligence. To understand how the brain produces intelligence is an ultimate problem for

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human, a challenge that most brains scientists even think that it cannot be solved for centuries or even thousands of years. That is to say, there is not a basic logic bridge to produce human level intelligence, as understanding is still in its infancy. This viewpoint is widely accepted, even for the opposition of this viewpoint, also share the basic assumption that “understanding intelligence” is needed before “making (such) intelligence”.

“Making intelligence” must base on “understanding intelligence”? Is it really true? This is possibly correct for weak AI such as computation, symbolic reasoning, and what Alpha Go does. However, it is not correct for the ultimate goal of AI, the artificial general intelligence. The reason is very straightforward: Setting “understanding the brain intelligence” as the premise means to solve a harder problem before “making artificial general intelligence”. This is logically wrong just like putting the cart before the horse.

However, if we move our attention from the traditional thinking to where is the biological intelligence from, we may find a “new” way to create the artificial general intelligence, following a “new” methodology named as Imitationalism. The underlying philosophy is “function comes from structure”, i.e., the same structures (with similar functional components) will generate similar functions. It is new just because it reverses the order of “understanding intelligence” and “making intelligence”. Understanding intelligence (the functions of the brain) is instead by analyzing its structure with advanced detection tools (so called brain reverse engineering). Then, imitate the brain by assembling neuromorphic devices (artificial neurons, synapses, etc.) according to the structure of the neural networks of the brain (so called physical imitation engineering). Finally, stimulate the artificial brain with signals from the environment and train it interactively to generate intelligence (so called intelligence fostering engineering). The brain reverse engineering, physical imitation engineering and intelligence fostering engineering are collectively called brain imitation engineering, likely to be realized in dozens of years. Although the three engineering are also very difficult to realize, they are easier than “understanding intelligence”, which is still unforeseeable and unreachable. The reason why the word “new” is quotation marked here is that the thinking of “function comes from structure” has been practiced for thousands of years, as a classic methodology for engineers. While the thinking of “understanding comes before practice” or “seeking scientific principle before any practice” is an ossified thinking formed in hundreds of years.

Imitationalism can be regarded as the fifth methodology for AI, following the symbolism, connectionism, behaviorism and statisticism. It has close relationships with the above four methodologies and is also a necessary step for the above four to achieve the ultimate goal of artificial general intelligence. The advanced intelligence of human basically results from complex neural network structure and the strong information processing capability of the cerebral cortex^[2]. The conventional computer, which implements

mathematical logic with switching circuit under Von Neumann architecture, is a good platform to realize specific intelligence such as logical reasoning, but not suitable to realize the artificial general intelligence. In fact, Von Neumann had not expected his architecture to become an AI platform when he developed it seven decades ago. On the contrary, he had carefully considered the possibility to design a new type of computer according to the neural system of the human brain.

Although the concepts of the artificial neural networks and the computer came into being basically in the same period, the exponential increasing performance of computer under the Moore’s law in the past half century gave people an illusion that the conventional computer is powerful enough to implement AI, which overshadowed the greatness of the thinking of neural networks. In fact, the top supercomputer nowadays could only simulate the functionalities of the brain by 1%, with very huge power consumption. Therefore, in order to imitate the brain as per the imitationism, it is required to design a totally new platform which could be called brain-like computer or neurocomputer^[3], which is a milestone of the brain imitation engineering and will be the corner stone to achieve the artificial general intelligence.

2 The “New” methodology

Before revealing the mechanism of the human brain intelligence, is it possible to make an artificial general intelligence? The answer is positive, and making such an intelligent machine may be the best shortcut to uncover the enigma of the human intelligence^[4, 5].

The human intelligence is the unique function of our living brain. As pointed out by Markram and Meier^[6] in the report on human brain project submitted to Europe Union (EU), “no other natural or engineered system can match its ability to adapt to novel challenges, to acquire new information and skills, to take complex decisions and to work reliably for decades on end. And despite its many diseases, no other system can match its robustness in the face of severe damage or match its amazing energy efficiency. Our brain consumes about 30 W, the same as an electric light bulb, thousands of times less than a small supercomputer.”

Understanding how the human brain produces intelligence (understanding intelligence) is the ultimate problem in the brain science. Similarly, making the human level intelligence (making intelligence) is the technical crown of engineering technology. If the problem of “understanding intelligence” could be solved, it will be naturally easy to realize “making intelligence”. But, we still know little about the human intelligence. In fact, “What is the biological basis of consciousness?” is listed in the top 25 big “What do not we know” questions by *Science* in July of 2005. The intelligence of the brain is from the dynamic behavior of the biological neural networks, while the mathematical and physical theory to handle it is not available. Therefore, putting our

hope for making intelligence on understanding intelligence is actually to base one problem on the solving of another more difficult problem, which misleads many researchers in the past 60 years’ history of AI. In order to make new progress in AI in the new era, we must break away from the traditional thinking and correctly position the relationship between the scientific problem (understanding intelligence) and the engineering problem (making intelligence).

2.1 Function comes from structure

The relationship between brain and awareness, or that of machine and intelligence, is just like the relationship between airplane and flying, or more simply, between glue and bonding, or that of flute and its sound. Here is the question: Is it necessary to understand the chemical principle underlying the bonding function before making any glue? Is it necessary to draw out the aerodynamic formula of the beautiful flute sound before making a flute? Obviously, we surely are not against that those flute makers hundreds years ago, even nowadays, do not understand aerodynamics. But if we are questioned whether it is necessary to study aerodynamics before making an airplane, the answer may be not so obvious as before. Undoubtedly, the plane designers in present times should learn aerodynamics. However, when Wright brothers designed the first plane of the world in 1903, there was not a subject on aerodynamics. Inspired by bird gliding, they succeeded on flying the first plane with a mechanical engine. In 1908, after having observed a short flight by Henry Farman in a test airplane in Paris, Theodore von Krmn started to believe the machine also could fly and “determined to make every effort to study the mystery about wind and flying in the wind”. 30 years later, he successfully established the aerodynamics with his student Qian Xuesen (Hsue-Shen Tsien) and answered the question of why the airplane could fly in the air.

It is the same with the relationship between “understanding intelligence” and “making intelligence”. To achieve a true humanoid intelligence, we must first distinguish the function of the brain function (intelligence, consciousness) from the structure of the brain structure (mainly neural networks of the cerebral cortex). Even though our objective is to realize intelligent functions, we need to go back to the structural level, i.e., to firstly make out the same structure and then test if it could produce the anticipated function. Just like as the engineering methodology, practiced by human beings for thousands of years, to make new devices such as a flute, a plane or the future general intelligent machines.

The human brain is so far the most complex structure known in the universe, but still a physical structure with limited complexity: hundreds of billions of neurons (10^{11}) in hundreds of kinds, each of which has several thousand or even ten thousand synapses which connect with other neurons (the total connection quantity may exceed 10^{14}). With neuroscience experimental approaches, the physico-

chemical property of neurons and synapses could be analyzed from the perspective of molecular biology and cell biology, and their characteristics on signal processing and information processing may be represented as mathematical models. For achieving the above goals, there is no obstacle that we cannot surmount. The neuron and synapse, as information processing unit, lay the lower bound for the structural analysis. With continuous advancing detection tools and increasingly sophisticated analytical approaches, mapping the structure of the brain is a realizable engineering.

The human brain, like a deep valley lying between us and the artificial general intelligence, is not a bottomless one. One reason for the bottomless feeling is that most AI research excessively focuses on the crown on the peak in the past. In 2008, the National Academy of Engineering of USA listed reverse engineering of the human brain as one of the major engineering problems of 21st century^[7]. Recently, more and more “Brain Projects” launched worldwide are offering more supports to high precision brain mapping. Therefore, we should not be entangled in the controversy on how the intelligence is produced, but try to make any possible breakthroughs in brain structure imitation based on the latest works on brain structural mapping. Once the brain imitating machine could produce some functions of the brain, the mystery of the brain may be unveiled in a foreseeable period.

2.2 Three steps to imitate the brain

The brain imitation engineering could be divided into three interrelated steps or three sub-engineering fields: the brain reverse engineering (BRE), the physical imitation engineering (PIE) and the intelligent fostering engineering (IFE). The fundamental task is to make out the brain-like machinery, or a neuromorphic computer, or neurocomputer for short. The neurocomputer is the machine which imitates the structure of the brain’s neural systems and its information processing mechanism, with the goal to produce artificial general intelligence.

The goal of the brain reverse engineering is to map the brain at structural level. That is, analyze the human brain as a matter or physiological object to make clear the functions of basic elements (various neurons and synapses) and their connection relations (network structure). This stage is mainly completed by neuroscience experiments and advanced analysis and detection technology. British physiologists, Alan Hodgkin (1914–1998) and Andrew Huxley (1917–2012) jointly put forward, in 1952, the famous Hodgkin-Huxley equation (HH equation)^[8] which exactly described the dynamic discharge process of single neuron and won the Nobel Prize in 1963. Tsodyks et al.^[9] jointly constructed computing model of synapse in 1998. In 2005, Swiss Federal Institute of Technology in Lausanne (EPFL) launched the blue brain program to approach the bio-realistic imitation^[10] of the cortical columns of specific

brain regions. In January 2013, Europe launched the human brain program by investing more than one billion Euros to combine information technology and life science, and integrate single molecule detection and entire brain structure analysis to realize the whole brain simulation^[11]. In April 2013, that is about three months later, Obama announced that 4.5 billion dollars would be invested in BRAIN Initiative^[12] to draw out the dynamic map of the human brain in twelve years^[13]. The relevant progresses show that significant breakthroughs may be achieved on structural mapping of the human brain in the coming decade.

The target of the physical imitation engineering is to make out micro-nano devices that could emulate the functions of neurons and synapses so as to construct the neural network system of human brain scale under the conditions of limited physical space and power consumption. The representative project of this kind is the systems of neuromorphic adaptive plastic scalable electronics (abbreviated as SYNAPSE) launched by defense advanced research projects agency (DARPA) in 2008 to develop a kind of electronic device with power consumption of 1 kW (that of the human brain is about 30 watts) that could match the human brain cortex in terms of function, scale and density, for which IBM and several universities were granted over 100 million dollars. On August 7, 2014, IBM^[14] released an article on *Science* to announce they successfully developed neuromorphic chip TrueNorth which contains 1 million neurons and 256 million synapses. This event was listed in “Top 10 Scientific Breakthroughs in 2014”. University of Heidelberg has amassed rich experience in development of neuromorphic chips over a dozen of years^[15, 16] and successfully integrated 200 thousand neurons and 50 million synapses on an 8-inch wafer in March 2015. Because the amount of synapses of the human brain is ten thousand times that of neurons, the synapse-imitating devices become a hot topic in the international research community. Recently, fast progresses are also made in memory resistors and optical synapses.

The main hardware of the neurocomputer is the large scale neuromorphic chip, which includes a neuron arrays and a synapse array, the former mutually connected through the latter. One typical connection structure is cross bar which enables one neuron to connect with one thousand or even ten thousand other neurons. This connection structure could be configured or adjusted by software. The basic software of the neurocomputer is mainly used for realizing the mapping of various kinds of neural networks onto underlying neuromorphic hardware. The “software neural networks” may copy from specific regions of the biological brain, or may be optimized or newly-designed neural networks based on the biological one.

The intelligent fostering engineering is about the application software of the neurocomputer, which aims to enable the neurocomputer to produce intelligence similar to the human brain or even self-awareness by applying information stimulation, training and learning. The stimulation may be the virtual environment, various kinds of information (e.g.,

big data from the internet) and signals (e.g., cameras and sensors of internet of things around the world) from the real environment, or exploration and interaction experience obtained by installing it on a robot body which can move in the natural environment. This method takes the methodology of behaviorism except for replacing the intelligence platform with the neurocomputer. By use of interactivity, the adjustment to connection relationship and connection strength of synapses of the brain-imitating neural networks is realized, to realize learning, memorizing, recognition, conversation, reasoning and other high level intelligence.

Imitationalism can be regarded as another methodology following symbolism, connectionism, behaviorism and statisticism, and has close relationship with the four. In particular, imitationalism can be regarded as extreme connectionism: the neurons, synapses and neural circuits all approach the biological counterparts as possible so as to repeat corresponding biological functions from the elements to the entire network. Although the classic artificial neural network is one form of connectionism, its measures are to the contrary: Use the simplified neuron models and human-designed network structure to produce complex functions; Although some functions may be realized, it is not known when the real human level intelligence could be produced. Imitationalism is to approach neural networks from the structural level, therefore it is more possible to produce the artificial general intelligence. The principle of the intelligence could be further studied after successful production of the intelligence. Certainly, simplifying or optimizing solution can be considered after full understanding of the intelligence, which is fully consistent with the technical engineering methodology that has been practiced for thousands of years.

2.3 Towards AGI: Conventional computer versus neurocomputer

It is well known that the conventional computer is based on mathematical logics and the switching circuit theory. In 1936, to prove the existence of the “incomputable number”, Alan Mathison Turing proposed a universal computing machine that only processes binary symbols (0 and 1) and could also imitate any mathematical reasoning process, which is widely regarded as the origin of modern computers. In 1938, Claude Elwood Shannon (1916–2001) established the theory of switching circuits which bridges mathematical logics with the physical implementation. In 1946, the first computer ENIAC was successfully developed, which, in essence, is a large mathematical logic circuit system made up with about 18 thousand electronic tubes. In the same year, John von Neumann (1903–1957) put forward the storage program architecture with storage and computing separated (called Von Neumann architecture) which actually is the physical embodiment of Turing machine. By the end of 1947, Bell Labs invented the transistor which became a smaller and more efficient substitute for the vac-

uum tube. In 1952, the first computer of Von Neumann architecture (EDVAC) came into being which only used 2300 electronic tubes but increased its performance by ten times that of ENIAC. In 1954, Bell Labs successfully assembled the first transistor-based computer TRADIC, which signaled the coming of large-scale integrated circuit transistors into our world and then the computer performance increased at an exponential rate under the Moore’s law.

The conventional computer based on Turing model has, on one hand, its theoretical limits (“incomputable number”) and on the other hand is a kind of general computing tool which could help realize various applications. Is it possible to realize the human level intelligence since the computer could be used as a platform to realize various intelligent applications? Or, could all the intelligence of the human brain be computed? This is a question that has not been answered theoretically till now. Could the neurocomputer realize all the intelligence of the human brain? Is the neurocomputer still a Turing machine? Both of the questions above are also pending till now. In that case, why should we make the neurocomputer? Why not to continue using computers as a platform to realize stronger intelligence or even the strong AI?

The neurocomputer does not preclude using computers continuously as a platform to develop stronger intelligence or the strong AI. However, the information processing on the conventional computer is based on the one-dimension instructions sequences, and for each instruction, one or more data may be fetched from and stored into the memory. The biological neural network, as a parallel system which processes the spiking trains asynchronously, can generate complicated non-linear behaviors. Even the neurocomputer is theoretically proved to be a Turing machine in the future, it is still necessary to process the dynamic multi-dimension information more efficiently. As transforming such tasks to one-dimension instructions stream and then executing on the conventional computers will cost extremely much (hardware scale and power consumption), or even not achievable in finite time.

Von Neumann is the person who best knows about the advantages and disadvantages of the computer architecture he proposed. Subsequently, the computer of the Von Neumann architecture is developed at an unprecedented speed, which forced him to concentrate his efforts onto the design and implementation of the computer, for which he was later widely reputed as the father of computer. However, Von Neumann did not think as later generations that his architecture is excellent enough to be used as the platform for AGI, so in his last years, he continued to study how to use unreliable components to design a reliable automata and how to design a self-reproductive automata. As Von Neumann was hospitalized for cancer in April 1956, it was impossible for him to give his points, in that summer, to Dartmouth summer research project on AI, which marked the advent of the new subject. One year after the death of Von Neumann, the book *The Computer and The Brain* was compiled based on his uncompleted documents

for the Silliman lecture for Yale University and published in 1958^[17], about more than half of which was describing neurons, nerve impulse, neural networks and information processing mechanism of the human brain.

Alan Turing, widely reputed as “Father of Theoretical Computer” and “Father of AI”, also did not regard the computer as the natural platform for realizing real intelligence. In October 1950, Turing showed his thinking for making intelligent machine in his article titled “Computing Machinery and Intelligence”^[18]. Turing thought the real intelligent machine must be able to learn. He described how to make such machine by taking human development as a model: Simulate the child brain firstly, then educate and train it. Consequently, Turing did not concentrate on the computer as Von Neumann, and came into mathematical biology. In 1952, Turing released an article titled “Chemical Basis for Morphogenesis” in which he used “chemical reaction-diffusion equation” to explain the development of patterns and shapes in biological organisms (this hypothesis was verified by experiments 60 years later). For this reason, Turing became the founder of morphogenesis theory. If he did not pass away so early, it is basically sure that he would make great contributions to dynamic analysis of neural networks of the human brain, and the neurocomputer imitating the human brain would also come out earlier.

Following the Moore’s law, conventional computer has been developed very fast for half a century. The great success of computer applications overshadowed the shortcomings of the Von Neumann architecture. The architecture is characterized by separation of memory and processing unit. The key advantage of the design is the software could be programmable, namely, different software could be loaded in the same hardware platform to implement different functions; at the same time, this is its key disadvantage, that is the huge communication cost between the memory and the processing units, which negatively affects its performance and results in the problem called “memory wall”^[19]. Comparatively speaking, the human brain has the following characteristics and advantages: high error-tolerance (tolerate the deaths of large numbers of neurons while keeping its basic functions normal), high parallelism (about 10^{11} neurons), high connectivity (more than 10^{14} synapses), low computing frequency (about 100 Hz), low communication rate (several meters per second), low power consumption (about 20 watts). A researcher proposed an index for comparing the performance of the human brain and the computer^[8]: the number of traversed edges per second (TEPS) on a large random graph. Its basic thinking is that the performance bottleneck of the human brain is not computing but communication between neurons; and one impulse used for communication between neurons is similar to traversing one edge on the graph. Based on the TEPS index, the human brain is about 30 times faster than the existing fastest computer in the world^[20].

Table 1 is a comparison of the emerging neurocomputer with conventional computer from the classic perspectives.

Table 1 Comparison of the conventional computer and neurocomputer

	Conventional computer	Neurocomputer
Components	Transistor to construct switching circuits	Neuromorphic devices to imitate biological neurons and synapses
Architecture	Turing model Von Neumann architecture	Based on biological neural networks
Hardware	Arithmetic logic unit Control unit Registers Data and control bus	Neuron array Synapse array Routing bus
Basic software	Operation system Compiler	Neuromorphic array configuration Mapping neural networks to neuromorphic array Dynamic behaviors management
Application software	Data structure + algorithm = (artificial) program	(Big) data + training algorithm = (autonomous) learning
Typical functions	Calculation Logical and structural data processing	Structure discovery from non-structural sensing and perception
Target intelligence	Artificial intelligence	Autonomous intelligence AGI
Science base	Cognitive science	Neuroscience

2.4 Why not the artificial neural network?

The human intelligence is produced by neural networks of the human brain, therefore it is a natural idea to choose the artificial neural network to imitate the neural networks of the human brain. The idea can be traced back to the mathematical model of neurons proposed by neurophysiologist Warren Sturgis McCulloch and the scientist of mathematical logician Walter Harry Pitts in 1943. In their seminal paper entitled “A Logical Calculus of Ideas Immanent in Nervous Activity”, they proposed a simple formalized neuron often called as McCulloch-Pitts neuron, which is still the standard of reference in the field of artificial neural network.

In March 1955, the Western Joint Computer Conference (WJCC) was held in Los Angeles, where Walter Harry Pitts chaired a session on learning machine. During the session, two participants, Oliver Selfridge and Alan Newell, also presented the Dartmouth AI meeting one year later, respectively published a paper on pattern recognition and another paper on the possibility for computer to play chess, from two different viewpoints. Walter Pitts summarized the session that “(one viewpoint) tries to imitate the nervous system, while Mr. Newell tries to imitate intelligence ... but both of the viewpoints are leading to the same target.” This laid a start point to fight against each other for the approaches of “structure” and “function” in the following decades^[21, 22].

Comparing with the transistor which boosted the computer for decades, the lack of neuromorphic devices confined the steps of neural networks. In 1940s, people had as much enthusiasm to neural networks as to the computer. Many researchers were studying the relationship among neuroscience, information theory and control theory, and used the simple networks to make some robots, the most famous

of which is the Tortoise made by William Grey Walter. It is known that IBM produced the first electronic computer IBM701 in 1953, but it is little known that IBM invented neural networks containing 512 hardware neurons in 1956. In 1957, Frank Rosenblatt invented the “perceptron” algorithm at the Cornell Aeronautical Laboratory. The perceptron was intended to be a physical machine, rather than a program, while its first implementation was in software for the IBM 704. It was subsequently implemented in custom-built hardware as the “Mark 1 perceptron”. This machine was designed for image recognition: It had an array of 400 photocells, randomly connected to the “neurons”. Weights were encoded in potentiometers, and weight updates during learning were performed by electric motors. In the 1960s, Bernard Widrow and Ted Hoff developed adaptive linear neuron (ADALINE) which used electrochemical cells called memistors (memory resistors) to emulate synapses of an artificial neuron. The memistors were implemented as 3-terminal devices operating based on the reversible electroplating of copper such that the resistance between two of the terminals is controlled by the integral of the current applied via the third terminal. The ADALINE circuitry was briefly commercialized by the Memistor Corporation in the 1960s enabling some applications in pattern recognition. However, since the memistors were not fabricated using integrated circuit fabrication techniques, the technology was not scalable and was eventually abandoned. Consequently, limited by high costs for making electronic neural devices, no visible progress was made in making the large-scale physical neural networks.

In 1982 and 1984, John Hopfield, a famous biophysicist of USA published two articles about the artificial neural networks, which reminded the people again to dig the power of neural networks. In 2006, Hinton and Salakhutdinov^[23] proposed deep belief networks in the paper published on

Science, which triggered the return of the artificial neural networks and the third AI revolution featured with deep learning.

Except for the lack of neuromorphic devices to imitate the biological ones, the neuron and synapse model employed by the artificial neural networks are too simple to match the biological one, in at least three aspects. Firstly, the mathematical model of bio-neurons, say the Hodgkin-Huxley equation, is much more complex than that of the artificial neural networks. Secondly, the human brain is a kind of extremely complex bio-tissue that is made up of about one hundred billion neurons of different types, which are mutually connected through several thousand or even ten thousand synapses for each. There are still two orders of magnitude gap to imitate the human brain with the top high performance supercomputer in the world, even with a simplified neuron model. Thirdly, biological neural networks use action potential to represent and convey information and process the information as per nonlinear dynamic mechanism. The existing artificial neural networks including deep learning networks still have not such dynamic features. In order to make stronger intelligence or even the artificial general intelligence, it is necessary to emulate bio-neural network system in structure and elements more accurately.

3 Progress of neurocomputer

Neurocomputer, or the neuromorphic computer in more formal sense, is an intelligent machine constructed according to structure of the neural networks in the brain, with neuromorphic devices which imitate the functionalities of the biological neurons and synapses, to implement brain-like intelligence and artificial general intelligence.

The concept of brain-like machinery could be traced back to Gerald Maurice Edelman (1929–2014), who shared the 1972 Nobel Prize in physiology or medicine for work with Rodney Robert Porter on the immune system. Soon after that, Edelman^[24] turned his interest to the theory of consciousness, documented in a trilogy of technical books and in several subsequent books. In his books, Edelman argued that the mind and consciousness are purely biological phenomena, arising from complex cellular processes within the brain, and that the development of consciousness and intelligence can be explained by Darwinian Theory^[25, 26]. To verify his so-called synthetic neural modeling theory^[27], Edelman led the developing of the brain-based-devices (BBD)^[28–31], the Darwin series of neural automata from 1981. BBDs were originally software models, they have had physical bodies that interact with the environment from 1992. The body known as neurally organized mobile adaptive device (NOMAD) platform, developed in 2000, has many sensors, such as a pan-tilt color camera for vision, artificial whiskers for texture sensing. Darwin X and Darwin XI (2005–2007) investigated a hippocampal model of spatial, episodic, and associative memory that learned to

navigate both open-field and maze environments, by simulating the medial temporal lobe and surrounding cortical regions (100 K neuronal units, 1.2 M synapses). In 2005, a special scientific version of BBDs, granted by DARPA, was undefeated in a series of exhibition games against the classic AI-based robots from Carnegie Mellon University at the US Open RoboCup in Atlanta.

Also early to 1980s, Professor Carver Mead of CalTech, a pioneer of modern microelectronics, began to explore the potential for modelling biological systems of computation, for both animal and human brains, and pioneered the neuromorphic engineering concept and practices. Mead predicted correctly that the conventional computer would use ten million times more energy (per instruction) than the brain uses (per synaptic activation). Observing graded synaptic transmission in the retina, Mead became interested in the potential to treat transistors as analog devices rather than digital switches^[32]. He noted parallels between charges moving in metal oxide semi-conductor (MOS) transistors operated in weak inversion and charges flowing across the membranes of neurons^[33]. Mead^[34] succeeded in mimicking ion-flow across a neuron's membrane with electron-flow through a transistor's channel, the same physical forces are at work in both cases. He worked with Professor John Hopfield and Nobelist Richard Feynman, helping to create three new fields: neural networks, neuromorphic engineering, and the physics of computation^[35]. During the 1980s, Mead led a number of developments in bio-inspired microelectronics, culminating in the publication of his book entitled *Analog Very Large Scale Integration (VLSI) and Neural Systems* in 1989^[33]. In May 1989, Mead co-chaired a *Workshop on Analog Integrated Neural Systems* on working chips in this area, in connection with *International Symposium on Circuits and Systems*. The authors listed in the published proceedings^[36] are still leading figures in neuromorphic engineering and/or related areas of research till to now. Also from 1989, Mead started to advise Misha Mahowald, a Ph. D. degree candidate in computation and neural systems, to develop the silicon retina, using analog electrical circuits to mimic the biological functions of rod cells, cone cells, and other non-photoreceptive cells in the retina of the eye^[37]. In 1992, Misha was awarded the Ph. D. degree in computational neuroscience, a symbol of the emerging subject, with her prized thesis for its originality and “potential for opening up new avenues of human thought and endeavor”.

Kwabena Boahen, who has also participated in the development of the silicon retina^[38] when he was a Ph. D. degree candidate supervised by Mead from 1989 to 1997, developed the Neurogrid from 2005 in the “brains in silicon” laboratory established by him at Stanford University. Neurogrid uses subthreshold analogue circuits to model neuron, with a quadratic integrate and fire model, and synapse dynamics in biological real time^[39]. Each neurocore, which integrates 65 536 sub-threshold analogue neurons on chip, includes a router that is able to route spike packets between its local chip, its parent chip, and its two child chips via

digital communications. The neurogrid system comprises a software suite for configuration and visualisation of neural activities.

The IBM TrueNorth chip is the outcome of a decade of work under the DARPA SYNAPSE program aimed at delivering a very dense, energy-efficient platform capable of supporting a range of cognitive applications^[40]. The key component is a very large, 5.4 million transistor 28 nm complementary metal Oxide semiconductor (CMOS) chip that incorporates 4096 neurosynaptic cores where each core comprises 256 enhanced LIF (leaky integrate and fire) neurons each with 256 synaptic inputs^[41]. The chip is all digital, and operates asynchronously apart from a 1 kHz clock that defines the basic time step. TrueNorth chips can be connected directly together to form larger systems, and a circuit board with 16 chips has been developed, incorporating a total of 16 million neurons and 4 billion synapses. Larger systems can be assembled by connecting multiple boards together. The hardware behaves deterministically exactly as predicted by a software model, which can therefore be used for application development and to implement learning algorithms. The philosophy underpinning the TrueNorth support software is to raise the level of abstraction at which applications are conceived from the level of the individual neuron to the level of cognitive modules, where each module occupies one neurosynaptic core, and a library of such modules can be pre-generated and made available with tested and tried performance and behavior.

The BrainScaleS neuromorphic system has been developed at the University of Heidelberg over a series of projects funded by the European Union, including the fast analog computing with emergent transient states (FACETS) projects and the BrainScaleS project. Ongoing support for BrainScaleS comes from the EU ICT flagship human brain project. BrainScaleS employs above-threshold analogue circuits to implement the AdExp (adaptive exponential integrate-and-fire) neuron model^[42], contrasting with the subthreshold circuits favoured by Carver Mead and used in the Stanford Neurogrid, and yield much faster circuits, running at 10 000 times biological speeds. Accordingly, BrainScaleS uses wafer-scale integration to interconnect the neurons very efficiently to accommodate the 10 000 times speedup^[43], in which each of the 48 reticles holds eight HiCANN (high-count analogue neural network) die, each of which implements 512 neurons and over 100 000 synapses. The primary communication layer in the BrainScaleS system operates within a wafer through hi-speed serial channels, each convey the output of 64 neurons from one HiCANN die to another. These high-speed channels pass through cross-bar switches to route the channels across the wafer. The support software for BrainScaleS is PyNN^[44], a python-based neural network description language. PyNN not only specifies the network but can also define the network inputs and how the user wishes to visualise the outputs, offering a sophisticated environment for specifying and managing neural network modelling. At the end of

March 2016, a 20-wafer BrainScaleS platform incorporating 4 million neurons and 1 billion synapses running at about 10 000 real-time was released for open access by The EU Flagship Human Brain Project (HBP) to the scientific community, to accelerate progress in neuroscience, medicine, and computing.

The SpiNNaker from the University of Manchester, grounds on the advanced reduced instruction set computer (RISC) machine (ARM) architecture, is a massively-parallel digital computer whose communication infrastructure is motivated by the objective of modeling large-scale spiking neural networks with connectivity similar to the brain in biological real time^[45]. The current largest SpiNNaker machine (available as another EU HBP platform) incorporates 500 000 processor cores, with a goal of doubling this to a million cores over the coming year. Brown et al.^[46] describes the (rather unusual) low-level foundation software developed to support the operation of the machine.

The above mentioned Neurogrid, BrainScaleS, TrueNorth, SpiNNaker and other neuromorphic systems shape the profile of nowadays' neurocomputer, the novel neuromorphic devices will form its future, as to imitate human brain means to integrate 10^{11} neurons and 10^{14} synapses in a limited physical space and with low energy consumption^[47]. As mentioned above, the neuron model is LIF for IBM TrueNorth, adaptive quadratic IF for Neurogrid, more accurate AdExp for BrainScaleS and programmable, thus possible to approximate the HH equation, for SpiNNaker and any software-based system on high performance computer. In August 2016, IBM scientists in Zurich announced they create world's first artificial neurons with phase-change materials^[48], if practicable, a big step to physical neuron.

Compared with emulating the bio-neuron, a bigger challenge is to invent the physical device to emulate the bio-synapse. The synapse between neurons is not a simple connection but a place where memory and learning happen. The human brain contains up to 100 TB synapses, tens of thousands of times more than the number of neurons. If the synapse is emulated with the static random access memory (SRAM) and each synapse occupies 8 bit, 100 TB SRAM is required. The Tianhe-2 supercomputer only contains 144 TB dynamic random access memory (DRAM). Therefore, the physical device whose size is smaller than transistor and functional characteristic is close to that of biological synapse, is necessary for brain-level imitation on neurocomputer.

Memristor, also called memory resistance, seems to be born for synapse imitating. This concept is introduced by Leon O. Chua, a Chinese scientist at the University of California, Berkeley, in his paper *Memristor—the Missing Circuit Element* in 1971. In 2008, HP Laboratory introduced resistive random access memory (RRAM) made by titanium dioxide to reproduce the functionality of the memristor^[49]. In 2009, HP proved that Crossbar Latch can be used to implement stacked-3D memristor array easily. The switch

between wires is about 9 square nanometers, and the switch time is less than 0.1 ns. In July 2011, Samsung announced a great breakthrough in RRAM technology. In 2013, Dr. Andy Thomas and his colleagues from Bielefeld University stated in a paper that memristor can continually increase or decrease resistance to emulate the learning and forgetting process of the artificial brain. In January 2014, Leon O. Chua published *Brains are Made of Memristors*, whose main idea is that the response characteristic of synapses is highly similar to that of memristors. HRL laboratories, also got the support from DARPA SyNAPSE project, used memristors to simulate synapses from the beginning and has more emphasis on the approximation of biological nervous system, especially the flexibility and programmability of neural connections as well as the learning ability. Narayan Srinivasa, the SyNAPSE chief researcher of HRL laboratories, said that their neuromorphic architecture uses abundant programmable brain-like connections, and they are currently focused on building a 2D cross matrix to reduce the risk to the limits, but they will extend the array to 3D in the future to simulate real synaptic structures found in the brain. According to the public information, HRL neuromorphic chip contains 576 neurons and 73 000 synapses, and its power consumption is 120 mW/cm². IBM also implied the possibility of using memristors in the future in the paper about TrueNorth chip in 2014.

From 2008, memristors^[48–53] and phase-change memory^[54–58] with intrinsic similarities to biological synapses attracted worldwide attention. Especially, the contributions from China, including Peking University^[59–62], Tsinghua University^[63–66], Nanjing University^[67–70], Chinese Academy of Sciences^[71, 72], Huazhong University of Science and Technology^[73–77] and National University of Defense Technology^[78–80], demonstrate the potential impact to this area from China. Although these devices do not feature in current large-scale neuromorphic systems, they may fundamentally change the landscape of the neurocomputer in the future.

In recent years, brain-mapping initiatives have been popping up around the world. The Human Brain Project of the EU, the Brain Research through Advancing Innovative neurotechnologies (BRAIN) of the United States, the brain mapping by Integrated Neurotechnologies for Disease Studies (Brain/MINDS) of Japan, the Brain-mapping Project of Korea and the brain science and brain-inspired intelligence technology project of China, successively debut, with the sharing goal of mapping the brain. To efficiently join forces, the Global Brain Workshop 2016, convened in the April of 2016, identified three grand challenges. The anatomical neurocartography of the brain, as the first challenge, exactly is the foundation of the Neurocomputer. According the opinion of the experts of the workshop, “within a decade, we expect to have addressed this challenge in brains including but not limited to drosophila, zebrafish, mouse, and marmoset, and to have developed tools to conduct massive neurocartographic analyses”^[81]. As if to prove

the expectation, half year later, Ryuta Mizutani and Pals at Tokai University in Japan complete an accurate 3D map of a drosophila brain’s neural network, with about 100 K neurons^[82].

4 Conclusions

To make artificial general intelligence by imitating the human brain is not a new idea. As capturing some features of the biological counterpart, the artificial neural network demonstrated significant advantage on making more and more powerful artificial intelligence. However, at least three barriers constrained artificial neural network to make artificial general intelligence: the too simple neuron and synapse model, the human designed network structure and the lack of dynamic behaviors.

Along with the inventing of the neuromorphic devices which can imitate the bio-neuron and synapse more accurately in the last decade, making hardware neural network to imitate the biological neural networks is becoming possible. The neurocomputer based on neuromorphic hardware is taking on the mission to make the artificial general intelligence. There are various differences between the conventional computer and the neurocomputer. Among them, the most prominent is the form of the information to be processed. In Turing’s model, which is inherited by the Von Neumann architecture, the data and instructions both are represented as one dimension sequence, which is essential to prove the existence of the “incomputable number”, also fine to implement arithmetic calculation and logic inference, but not enough to represent the dynamic 3D world and other more complicated forms, including the high dimension virtual worlds imagined by the human brain. In contrast, the neurocomputer, which duplicates the biological neural network, can handle the spike trains just like a brain. That is, the neurocomputer can process the spatial-temporal information in a dynamic way, which can not only cut off the huge energy consumption on information transform and exchange between the processor and the memory of the conventional computer, but also and more importantly, to reserve the dynamic nature of the information to create real intelligence for which the dynamic is indispensable. Therefore, the neurocomputer, but not the conventional computer, is the essential platform to achieve the artificial general intelligence.

The AGI is not the final destination of the neurocomputer, but a start point to explore the secret of consciousness. Neuroscientists have even proposed, “Perhaps the greatest unresolved problem in visual perception, in memory, and, indeed, in all of biology, resides in the analysis of consciousness”^[83]. Zhang and Zhou^[84] even designed simulation experiments to emulate self-consciousness, and indicated that self-consciousness can be imitated by machines. Obviously, the emerging neurocomputer will be an ideal platform to dig such exploration deeper and deeper. In return, such exploration will inspire new idea on opti-

mizing the neurocomputer's architecture deriving from the biological brain.

The conventional computer leads us into the information age via increasing performance and information processing capacity, the neurocomputer will lead us into the intelligence age via supporting the autonomous intelligence and even artificial general intelligence. Although the neurocomputer is still very primitive nowadays, once succeed, it may make the machine as intelligent as, even surpass, our human beings^[85]. Do not underestimate the neurocomputer, just as what should not have been done when the computer was invented in 1940s. The wise decision is to follow Alan Turing's suggestion at the end of his paper on "Can machines think?"^[19], that is:

We can only see a short distance ahead, but we can see plenty there that needs to be done.

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