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Intelligence Originating from Human Beings and Expanding in Industry — A View on the Development of Artificial Intelligence

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Abstract: Artificial intelligence (AI) aims to simulate the intelligent behaviors of the human brain, including information storage and processing mechanisms, providing machines with a certain level of intelligence. With the rapid development of a new generation of information technology, such as the Internet, big data, cloud computing, and deep learning, AI research and applications have made, and are continuing to make, significant progress. An intensive study of the historical integration and evolution of computer science, control science, brain-inspired intelligence, human brain intelligence, and other disciplines and fields closely related to AI, is presented in this paper. It is pointed out that research results on the structure and functional mechanism of the brain, from neuroscience, brain science, and cognitive science, provide important inspiration for the construction of an intelligent computing model. Moreover, several aspects of the foundations and development of AI are discussed, including the logical model and system, the neural network model, and the visual nerve hierarchy mechanism. Finally, developmental trends are predicted for the following five aspects of AI: the computational theory of the Internet, integration of AI reasoning and computation, model and mechanism of brain-inspired intelligence, impact of AI on neuroscience, and algorithm design for the feedback computation and energy level of control systems.
Keywords: artificial intelligence; human brain intelligence; brain-inspired intelligence; intelligence development; discipline evolution

1 Introduction

Artificial intelligence (AI) is a research field closely related to computing and control sciences. Since the 1970s, AI has been one of the world's three leading technologies (with space technology and energy technology), as well as one of the three leading technologies (with genetic engineering and nanoscience) of the 21st century. With the continuous development of information technology and its penetration into production, life, and economic and social development, especially with the rapid development of new generation information technologies, such as the Internet, big data, and cloud computing, AI now simulates the intelligent behavior of the information storage and processing mechanisms of the human brain, enabling the machine to have a certain level of intelligence. At present, AI research is making important progress, particularly in the discovery of complex structures in high-dimensional data. Deep learning is being applied to science, business, and government, and has played a significant role in promoting the development of information science.

This paper analyzes AI in depth and interprets its developmental process in two dimensions. The first dimension

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is the horizontal perspective: it traces back to the sources of neuroscience and human brain intelligence, discusses the important developmental process of each branch of AI, and comprehensively analyzes the development and evolution process of AI. The second dimension is a vertical perspective, from several disciplines closely related to AI, including computer science, control science, human brain intelligence, and brain-inspired intelligence. Through the interaction between these and AI in different historical periods, the blending and historical evolution of the listed disciplines are analyzed to help improve understanding of the nature of AI development.

2 Definition and historical evolution of intelligence

2.1 Definition of intelligence

In the field of psychology, intelligence is the general term used to define intellect and ability. Of these, “intellect” refers to the psychological characteristics of cognitive activities, and “ability” refers to the psychological characteristics of actual activities [1]. The following paragraph discusses the definition of intelligence through three aspects: human brain intelligence, AI, and brain-inspired intelligence.

The human brain is a complex biological network of more than 100 billion highly interconnected neurons, and is the source of human analysis, association, memory, and logical reasoning. Human intelligence reflects the wisdom and ability of the human brain to perceive, understand, and manage the world. Its research focuses mainly on the laws of human intelligent activities and has revealed the brain’s information representation, transformation mechanism, and learning rules, to establish an intelligent computing model of brain information processing. With the development of neuroanatomy, the mysteries of human brain information processing are gradually being revealed, allowing AI to be defined as the basic theory, method, and technology that simulates the intelligent behavior of the human brain by information processing, memory, and logical reasoning. By applying computer software and hardware technology, an artificial system with some degree of intelligence is constructed, so that the computer can perform tasks that previously required human intelligence. In contrast, brain-inspired computing aims to develop fast, reliable, and low-cost computing techniques by simulating the mechanism of the human nervous system. With research results from neuroscience, brain science, and cognitive science, the goal of “brain-inspired intelligence” is to establish an intelligent computing model that allows a machine to grasp the laws of human cognitive behavior.

2.2 Historical evolution of intelligence

In 1950, a landmark paper by Alan Turing (known as the father of AI) asked, “Can machines think?” This laid the foundations for a new discipline: AI [2]. At the Dartmouth Conference, in the summer of 1956, a group of visionary young scientists, including John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon, cooperatively studied and explored a series of problems with machine intelligence and proposed the term “AI” for the first time, marking the official birth of AI. As an emerging science and technology, AI is closely related to the evolutionary process of information science, especially the computer and control sciences. In the development of AI, scholars with different academic backgrounds have reached their own understandings of AI and have introduced different viewpoints. This paper comprehensively analyzes the main evolutionary links with, and interactions between, computer science, control science, and AI in various historical period, as shown in Fig. 1.

First, for computer science development, a solid and strong theoretical foundation was established. In the 1930s, breakthroughs were made in computability theory, and four important computational models were proposed: lambda calculus, Turing machines, Gödel recursive functions, and Post systems. In theory, these models are equivalent in ability, with the Turing machine being most similar to human calculation, and, thus, becoming the theoretical basis of computing. In the 1950s, Noam Chomsky established the theoretical system of formal languages [3]. From the language, grammar, and machine models, the hierarchical division of computer science was established; this had a profound impact on computer science, particularly on programming languages and compilation methods. At the same time, the computational complexity of the 1960s and the program verification theory of the 1970s laid a solid theoretical foundation for the development of computer science. Another aspect is the development of computer technology. In the 1950s, John von Neumann proposed a computer architecture based on program storage, in which program instructions and data shared one storage space. In 1945, the first generation of computer, ENIAC, was born. The IBM360, a computer system announced by IBM in 1964, and caused a stir in the industry. Later, in the 1980s, IBM maintained its leading position. By this time, the theory and technology of a single computer were relatively complete. Subsequently, the Internet emerged in the 1990s: in contrast to the determinism and completeness of a standalone system, this system was nondeterministic, openly shared, and dynamic. In recent years, some new generation information technologies have emerged, such as the Internet of things (IoT), cloud computing, big data,

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and now the cloud platform. Hence, the computer system evolved from a standalone machine to a dedicated LAN system capable of sharing resources, before developing into the Internet, where resources can be integrated and shared, then gradually evolved into the era of network information services, in which resources are dynamically allocated and services are highly developed and shared.

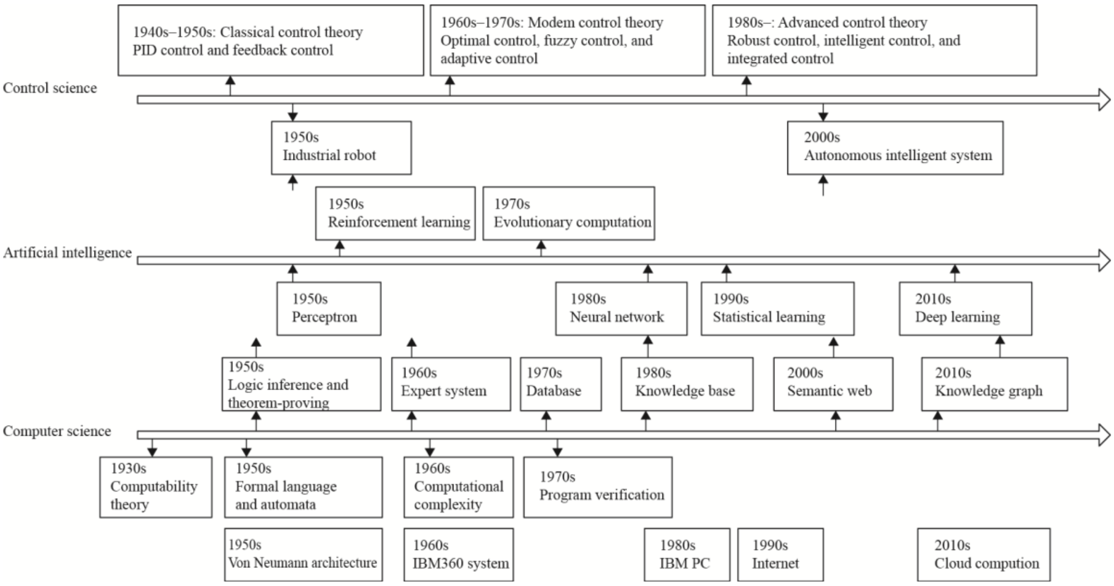

Fig. 1. Evolutions of computer science, control science, and AI.

Based on these theories and system developments of computer science, the evolution of AI can be traced back to the researches on logical reasoning and theorem proving represented by symbolism in the 1950s. Later, in the 1960s, the behavior of human experts was simulated and summarized into empirical rules to form rule-based systems and deduce the generation of knowledge in application fields. The expert system plays a very important role in many application fields, such as medical diagnosis and chemical logic relationship deduction. However, because the rules are manually formulated, once extracted, they are fixed, which is not convenient for the growth and expansion of the system. Because the rules are fixed, it is difficult for an expert system to deal with new problems. With this process, databases and knowledge bases appeared later, and a knowledge unit was established to support the deduction of rules; the semantic web organized the relationship among concepts to form a network. In addition to big data, the knowledge graph appeared. This simulates human logical thinking and was developed under the influence of computer science theories and system structures.

Another major approach to AI is connectionism, which simulates the cognitive processes in the human nervous system. The perceptron, proposed in the 1950s, was the first computational model to simulate the neuronal cells and synaptic mechanisms. Subsequently, the human nervous system was simulated, and artificial neural networks, such as the multilayer perceptron, were established. Until now, deep learning has also been developed using this approach.

Meanwhile, another important school in the development of AI, behaviorism, believes that intelligence is the interaction between the system and the environment. Therefore, intelligent methods, such as reinforcement learning and evolutionary computing, have been formed and can be regarded as a contribution of control science to AI. The development of control science has three important periods. In the 1940s and 1950s, classical control theory (PID control and feedback control) was introduced to control univariate and specific transactions and is based on trial and error. In the 1960s and 1970s, modern control theory (optimal control, fuzzy control, and adaptive control) emerged, establishing state equations based on the state space representation of linear systems, among which the Kalman filter is the most representative. After the 1980s, advanced control theory (robust control, intelligent control, and integrated control) appeared, represented by discrete event dynamic systems and hybrid systems. In addition, the robots that emerged in the 1950s were representative of this technology. Later, service robots appeared; in particular, autonomous intelligent systems, such as unmanned aerial vehicles, were recently introduced.

The above describes the situation and background of intelligence through three main lines. Another view, from the perspective of the development of computer science and brain-inspired intelligence, is shown in Fig. 2.

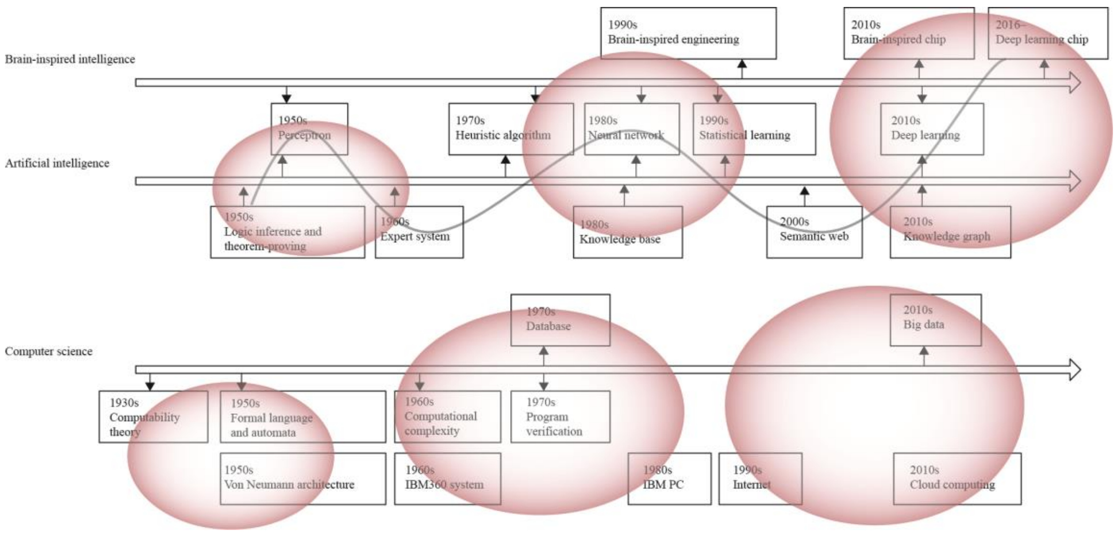

Fig. 2. Evolutions of computer science, AI, and brain-inspired intelligence.

Since the 1950s, AI has experienced three important waves. The first began in 1956, when symbolism used machine proof methods to prove and infer knowledge, and established logical theorem proving, expert systems, and knowledge-based systems. However, rules representing experts' experience were limited and definite, and it was difficult to update knowledge. At this stage, it had been expected that AI could solve many problems, but this was not the case, so AI then fell to a low ebb. The second wave was in the 1980s; promoted by the theory of algorithm complexity, a hardware support system, and database management systems, the connectionism represented by neural networks increasingly attracted attention from scholars. Multilayer perceptron and back propagation (BP) networks were proposed to successfully solve complex nonlinear classification and regression problems, which, again, led to an upsurge in AI. However, the computing power of machines was still very limited, there was a lack of powerful computing equipment and of an open learning environment, like human society, therefore, no source of a large number of data samples existed, as is required for neural network training. As a result, in the 1990s, neural network research reached a low ebb again. AI researchers turned their attention to statistical learning. The rise of the Internet, a nondeterministic and dynamic system, in the 1990s led to the emergence of cloud computing and big data. The Internet provides a more effective mechanism and platform for data acquisition and processing. In this way, the revival of neural networks was stimulated again, and the third wave, represented by deep learning, appeared. In 2006, Geoffrey Hinton proposed a deep learning algorithm for neural networks, which made it possible to train neural networks with at least seven layers [4]. Because the algorithm could better simulate the process of multilayer depth transmission of human brain neurons, it had a breakthrough performance in solving some complex problems. At the same time, research on brain-inspired intelligence gradually attracted the attention of academia and industry. The core of brain-inspired intelligence is to construct neuromimetic architectures and processors, including IBM TrueNorth and other hardware-based neuron chips, and deep learning chips, including the Google tensor processor unit (TPU) and the Cambrian series of the Chinese Academy of Sciences.

3 Foundations and development of intelligence

The structure and function of the brain, revealed by neuroscience, brain science, and cognitive science, provide important inspiration for the construction of an intelligent computing model. Based on the above analysis, this section traces back to the origin of intelligence and elaborates on intelligence-driven themes, including the logical model and system, neuron and network model, visual nerve hierarchical mechanism, spiking neural network model, learning and memory mechanism, language model, and evolution and reinforcement. Fig. 3 shows the "Five Lines Spectrum" of intelligence, in which the five lines represent five different areas, while the seven colors represent seven topics. The following subsections discuss the important developmental process of AI in these seven basic types of intelligence.

3.1 Logical model and system

The human nervous system has the potential for logical thinking. It can gradually form a specific logical thinking ability through acquired learning and training. Inspired by human logical thinking and the deduction processes,

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developments were made in logical reasoning and theorem proving during the 1950s to the early 1970s, up until the 1980s, when a large number of expert databases and knowledge bases appeared; the semantic web appeared in 1998, and the knowledge graph was proposed by Google in 2012. In this respect, by simulating human logical reasoning and learning ability, AI has undergone some important processes, such as logical reasoning and theorem proving, expert systems, knowledge bases, the semantic web, and knowledge graphs.

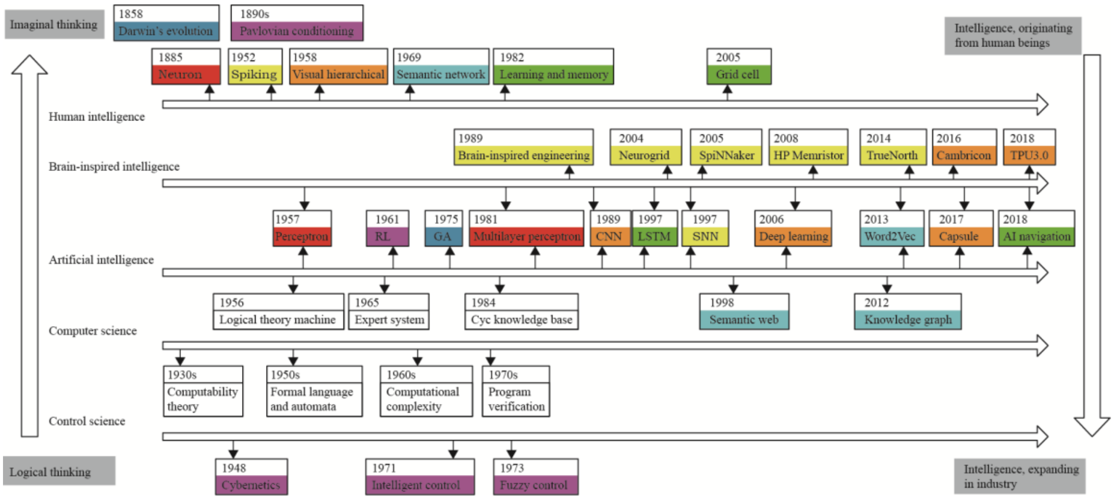

Fig. 3. "Five lines spectrum" of intelligence.

3.2 Neuron and network model

The human brain transmits information through neurons, and several neurons constitute a neural network. Inspired by a neuron and network model [5], the perceptron [6−8], which imitated the human neuron model, emerged in the 1950s. Subsequently, by simulating the process of human brain information transmission and processing, the multilayer perceptron [9], Hopfield network [10], and Boltzmann machine [11] were developed, causing a great sensation at the time. To solve complex learning problems, the BP algorithm [12], which can acquire the required information processing ability through learning, was developed to train multilayer neural networks. At this level, by imitating the structure and function of the biological brain, the AI field constructed an information processing system, and developed a series of important artificial neural network theories and methods, such as the perceptron, multilayer perceptron, Hopfield network, and BP algorithm.

3.3 Neural hierarchical mechanism

Inspired by the neural hierarchical mechanism [13], the typical achievements of exploring new neural network architectures are: the convolutional neural network [14], proposed in 1989 to simulate the information hierarchical processing mechanism of the human visual cortex; limited Boltzmann machine [15], which won the first prize in the million-scale ImageNet database in 2012; and the capsule network, a new type of neural network architecture proposed in 2017, which has made important breakthroughs in computing and intelligent simulation. Regarding deep learning algorithm chips, representative chips include the Cambrian series [16] and Google's TPU. At this level, based on the hierarchical information processing mechanism of the human brain, AI has developed a series of important deep learning models and frameworks, such as convolutional neural network, restricted Boltzmann machine, and capsule networks.

3.4 Spiking neural network model

Inspired by the signal transmission mechanism and synaptic plasticity rule of synapses between human brain neurons, a new spiking neural network model [17,18] and a neuromimetic architecture were explored. A representative achievement is the IBM TrueNorth [19] computer architecture, which realizes more efficient communication in parallel computing. A special electronic component, the memristor [20], has transmission characteristics very similar to synapses in the nervous system [21], and has the function of Boolean logic operation [22]. It has been used to construct multimemory synapses in pulsed neural networks [23]. At this level, based on the simulation of the higher biological nerve transmission mechanism, the AI field has developed a series of neuromimetic architectures, such as the spiking neural network, IBM's TrueNorth, and the memristor.

3.5 Learning and memory mechanisms

Inspired by learning and memory mechanisms, the long short-term memory (LSTM) network was proposed in 1997 to simulate the short-term and long-term memory mechanism of the human brain and nervous system [24]. In addition, neuroscientists have found that there are neuron location cells and grid cells in the brain and nervous system, which participate in brain memory activities. Inspired by this, the proposed grid-cell-based localization simulation system [25] can automatically generate grid patterns remarkably similar to brain cell activity, as well as help mice find shortcuts automatically. At this level, by simulating the ability of the human brain to acquire and store knowledge through learning, in the field of AI, LSTM and grid cell localization systems have been developed.

3.6 Language model

Inspired by the language model, the processing and coding mechanism for a machine's semantic information [26] have been explored to develop the semantic web and knowledge graph, which compose concepts and entities into a hierarchical network system. In addition, a statistical language model was explored, based on neural networks and visual alphabet recognition by the brain and nervous system [27]. The neural network language model (NNLM) [28], word embedding [29], and the letter recognition computing model based on the deep neural network [30], are extensively used in various natural language processing problems. At this level, based on simulating the human brain's ability to learn and organize language, AI has developed some important achievements, including semantic web, knowledge graph, NNLM, and word embedding.

3.7 Evolution and reinforcement

Inspired by the natural selection mechanism of "survival of the fittest" and the transmission of genetic information, methods, including genetic algorithms, evolutionary strategy, and ant colony algorithms, have been developed to search for the optimal solution through natural evolution. In addition, influenced by the development of control theory [31], optimal control methods, such as dynamic programming and Markov decision processes, have been devised. Q-learning, the SARSA algorithm, deep reinforcement learning network (DQN), and other reinforcement learning methods [32] were then developed to guide behavior through interaction with the environment. Based on the theory of biological evolution and genetics, genetic algorithm, evolutionary strategy, ant colony algorithm, and other evolutionary methods have been developed. Based on simulating the interactive learning process between human beings and the external environment, a series of important reinforcement learning methods have been developed, such as dynamic programming, Q-learning, the SARSA algorithm, and DQN.

4 Current status and trends in AI

4.1 Current status of AI

AI has been highly valued by governments around the world. In October 2016, the White House released a report, *National Artificial Intelligence Research and Development Strategic Plan*, which proposed seven strategies of AI that are prioritized in the United States, being: investment research and development (R&D) strategy, human-computer interaction strategy, social impact strategy, security strategy, open strategy, standard strategy, and human resources strategy; this raised AI to the national strategic level. In July 2017, the State Council of China issued the "New Generation Artificial Intelligence Development Plan," and proposed the guiding ideas, strategic objectives, key tasks, and guarantee measures for the development of China's new generation of AI in 2030. It deployed the first-mover advantage of building China's AI, to accelerate the construction of an innovative and powerful country in science and technology. In February 2017, the Chinese Academy of Engineering's "Frontiers of Information Technology and Electronic Engineering" published the "AI 2.0" issue, elaborating big data intelligence, group intelligence, cross-media intelligence, hybrid enhancement intelligence, and autonomy involved in AI 2.0 [33−39].

4.2 Development trends in AI

First, the characteristics of AI development must be recognized, as shown in Fig. 4. Traditional AI pays attention to the process from perception to cognition and achieves continuous improvement from logic to calculation. Current AI involves a system, from weak to strong, from closed-loop to open, from certainty to uncertainty. Future AI will be from rational to emotional, from finite to infinite, from specialization to synthesis. This process is more challenging, so the road to AI development is still exceptionally long. People are only recently beginning to make a deep effort to explore traditional AI, to lay the foundations for future AI.

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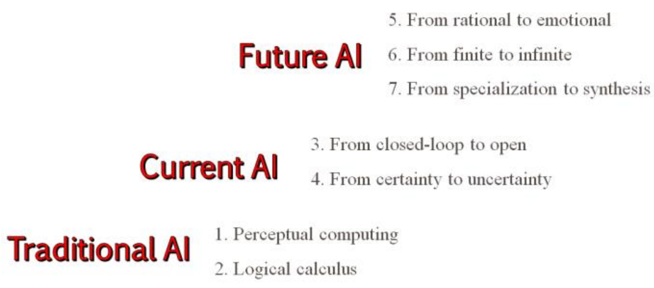

Fig. 4. Characteristics of AI development.

At present, AI's basic theory and technology have achieved a series of important research results. The following paragraphs present the remaining problems and challenges faced by future research in computer science, AI, brain-inspired intelligence, and human brain intelligence.

4.2.1 Computing theory of the Internet

Currently, continuous improvements and enhancements are being made to Internet infrastructure, application innovation, and business model innovation. Some preliminary application results have been achieved in the fields of intelligent transportation, Internet finance, and smart medical care. However, the study of Internet computing theory must be strengthened. The early standalone system has a solid theoretical foundation, while the Internet is an open and uncertain system, so establishing an Internet computing theory remains a big challenge.

4.2.2 Fusion of AI's reasoning and computation

Although deep neural networks have shown enormous success in tasks such as speech recognition and image recognition, the existing deep learning structure is far less complex than that of biological neural networks. The current neural network models mostly focus on the computational level of data. In fact, an advanced intelligent machine should be capable of both environmental perception and logical reasoning. Integration of the AI's reasoning and computation to reflect the alternately iterative process of the human brain will be the main research direction in the next step.

4.2.3 Model and mechanism of brain-inspired intelligence

During the construction of brain-inspired cognitive models, the neurons of spiking neural networks currently encode information in the form of electrical impulses; this is closer to the manner in which real neurons encode information, and can encode time information well. However, due to the lack of efficient learning methods in spiking training and the need to use substantial computational power, there remains a gap in the performance of deep network models. In future, the two types of models must continuously learn from brain science and continue to integrate, as well as develop a new generation of neural network models with better performance and higher efficiency.

4.2.4 AI's role in promoting neuroscience

As mentioned above, inspired by neuroscience, AI has reached the level of human-like efficiency in several tasks. Psychologists and neuroscientists have discovered and revealed relevant mechanisms of brain intelligence, which have stimulated the interest of AI researchers and provided preliminary clues. Additionally, quantitative formal research in the AI field provides insights into the requirement and capability of neuroscience research of brain intelligence. For example, based on the progress in machine learning, it was hypothesized that the human brain may be a hybrid optimization system, supported by a series of cost–function interactions [40]; this can provide novel clues for research in neuroscience. Therefore, the intersection of neuroscience and AI is expected to improve in the future, leading to a virtuous circle.

4.2.5 Algorithm design for feedback calculation and energy level of control system

The basic theories of computer science include the computability theory, computational complexity theory, and algorithms. These define whether a machine can calculate, the time (or space) cost of computation, and the design optimization of the algorithm, and have established computing theories for defining computability and evaluating cost. Moreover, the formal language automata theory defines four energy levels: finite automata, context-free automata, context-dependent automata, and Turing machine. This established an equivalence and hierarchical relationship between machine, language, and grammar, which has a profound impact, particularly on the design and compilation methods of programming languages. The advantage of control science is the feedback mechanism: the iterative gradient can be constantly corrected during the iterative process, thereby approaching the target. However, there is a lack of energy level theory in the design of the controller. In turn, the iterative computing process of the computer, from the starting point to the end, provides an iterative gradient, but there is a lack of feedback correction of the intermediate process. Therefore, continuous learning between computer science and control science will create more intelligent and effective theoretical methods that will be worth exploring and investigating.

5 Conclusion

Focusing on the development of AI and the main research achievements, this paper discussed the blending and historical evolution of computer science, control science, brain-inspired intelligence, human brain intelligence, and other disciplines that are closely related to AI. It explained the historical evolution of AI combined with the potential enlightenment of neuroscience on AI, including the logical model and system, neural network and model, and visual neural layering mechanism. Finally, it analyzed the development status of AI, and pointed out its characteristics and future developmental trends. The research results on brain structure and function revealed by neuroscience, brain science, and cognitive science provide important inspiration for building intelligent computing models, while formalization and modeling research of mathematics and physics, based on computation and control, support intelligent analysis and optimization, which are the industry of intelligence; the sum of these two components is AI.

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