Research on Brain and Mind Inspired Intelligence

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Abstract

To address the problems of scientific theory, common technology and engineering application of multimedia and multimodal information computing, this paper is focused on the theoretical model, algorithm framework, and system architecture of brain and mind inspired intelligence (BMI) based on the structure mechanism simulation of the nervous system, the function architecture emulation of the cognitive system and the complex behavior imitation of the natural system. Based on information theory, system theory, cybernetics and bionics, we define related concept and hypothesis of brain and mind inspired computing (BMC) and design a model and framework for frontier BMI theory. Research shows that BMC can effectively improve the performance of semantic processing of multimedia and cross-modal information, such as target detection, classification and recognition. Based on the brain mechanism and mind architecture, a semantic-oriented multimedia neural, cognitive computing model is designed for multimedia semantic computing. Then a hierarchical cross-modal cognitive neural computing framework is proposed for cross-modal information processing. Furthermore, a cross-modal neural, cognitive computing architecture is presented for remote sensing intelligent information extraction platform and unmanned autonomous system.

Keywords

I. Introduction

BRAIN and Mind inspired Intelligence (BMI) is an innovative bio-inspired computing based on bionics, which enlightened by cognitive function, neural structure and system behavior. BMI would realize state-of-the-art intelligence system which has advanced in computing ability, efficiency, and energy consumption. BMI will establish fundamental theories and models of neural cognitive computing, explore the algorithm and technology of the new generation computation, and research architecture and system of Artificial General Intelligence (AGI). The research contents of BMI include the intelligence scientific theory, brain-inspired algorithms and brain-like hardware for learning and processing.

Although BMI has been an obvious success at present, it is far from reaching the general autonomous intelligence level, and it lacks the ability of multimedia perception and cross-modal cognitive in both models and algorithms. For the study of the brain-inspired algorithm, which one is brain-inspired cognitive simulation from the global macroscopic functional, the other is reverse engineering the brain-like [1] neural structural emulation from the microscopic structures of neurons, synapses, and networks. However, there is still a lack of effective research how to assemble advanced function of the complex system from the local network in mesoscopic. There is still a long way to go to study the gap between natural intelligence and brain-inspired intelligence [2]. Until now, the study of the brain-inspired model has not supported the uniform mind function such as sensation, perception, cognition and behavior.

A. Key Contribution of the Paper

To address the problems of scientific theory, common technology and engineering application of multimedia and multimodal information computing, this paper is focused on the theoretical model, algorithm framework and system architecture of BMI based on the structure mechanism simulation of nervous system, the function architecture emulation of cognitive system and the complex behavior imitation of natural system.

(1) We reviewed the current state, key trends and outstanding issues of BMI from brain research projects, mind research projects, statistical learning, cognitive computing, deep learning and neuromorphic computing.

(2) Based on information theory, system theory, cybernetics and bionics, the related concept of brain and mind inspired computing (BMC) are defined, and the hypothesis, model and framework of the frontier BMI theory are proposed.

(3) A semantic-oriented Multimedia Neural Cognitive Computing (MNCC) model is designed for multimedia semantic computing based on the brain mechanism and mind architecture.

(4) A hierarchical Cross-modal Cognitive Neural Computing (CCNC) framework is proposed for cross-modal information processing.

(5) Furthermore, a Cross-modal Neural Cognitive Computing (CNCC) architecture is presented for remote sensing intelligent information extraction platform and unmanned autonomous system.

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The rest of the work is structured as: Section II provides a research background, which deals with a literature review, including studies of BMI, brain and mind research project, statistical learning, cognitive computing, deep learning and neuromorphic computing. Section III studies the relationship between the structure mechanism of the nervous system and the function architecture of the cognitive system, and then gives the definition of the BMI related concepts. Section IV gives the formal description and algorithm design of MNCC model and CCNC framework, and then gives the application results of engineering system based on CNCC architecture. Finally, we conclude our work and propose potential future work on this topic in Section V.

II. Related Work

A. Research Projects of Brain and Mind

With the development of Turing machine proposed in 1936 and the birth of first electronic computer ENIAC in 1946, the information technology has lay a foundation for realizing the dream of intelligent technology. However, since the concept of artificial intelligence was proposed in 1956, the related research fluctuates between success and failure. Many countries have made the significant investment in the scientific research of artificial intelligence in the past 66 years. Some initiatives and projects about intelligent behavior, brain and mind have been proposed respectively, such as Decade of the Brain (1990-2000), Decade of the Behavior (2000-2010) and Decade of the Mind (2012-2022). In addition, brain research projects of some countries have been launched successively, such as US BRAIN Initiative, EU Human Brain Project, Japan Brain/MINDS, China Brain Project, Brain Canada, Australian Brain Initiative, Korea Brain Initiative and Israel Brain Technologies, etc.

The neuroscience methods for studying the brain and the cognitive science methods for studying the brain tend to fuse and interact. Elucidation of the neural mechanisms in brain and cognitive processes in mind allows us to understand mind principles, and facilitates the intervention and diagnosis of neurological and psychological diseases. It also contributes to the research of frontier scientific theories, the development of key technologies and the application of engineering systems of BMI, and provides the basis for a next generation artificial intelligence with design beyond von Neumann architecture.

B. Cognitive Computing

The Bayesian theory has an indispensable role in the statistical learning. The Bayesian mechanism of the brain has been validated by a lot of experimental results in psychology and neurophysiology. According to Bayesian probability, causal inference, and statistical theory, it can simulate the perception and cognitive process of visual and aural, which can construct a unified cognitive theoretical framework.

As a successful technique and powerful method, cognitive computing has existed for a long time, but it has been making a breakthrough in recent years. Literature [3] seeks nothing less than to discover, demonstrate, and deliver the core algorithms of the macaque monkey brain. Watson system based on DeepQA and transfer learning to simulate cognitive processes of mind such as learning, thinking and decision making.

However, traditional cognitive computing focuses on the simulaton of mind function, and lacks in-depth research on the emulation of brain structure mechanism, which makes it difficult to realize general artificial intelligence. In addition, the role of belief in automatic reasoning is worth exploring [4].

C. Neuromorphic Computing

There are two main ways to build general artificial intelligence, namely Brain-Inspired Computing (BIC) and Brain-Like Computing (BLC). BIC simulates and designs intelligent model inspired by top-down brain function, including Artificial Neural Network (ANN) and deep learning. BLC emulates bottom-up brain structure to realize intelligent system. NeuroMorphic Technologe (NMT) includes three main forms: NeuroMorphic Engineering (NME) of neurons is established by sub-threshold analog circuit, NeuroMorphic Computing (NMC) [5] of spiking neural network is realized by digital system, and NeuroMorphic Device (NMD) of spiking neural network memristor-based [6] is constructed with new memory materials.

Carver Mead envisioned build neuromorphic electronic systems based on analog VLSI (very large scale integration) circuits, which established a new paradigm in hardware computing of BLC [7]. Guided by brain-like 'spiking' computational frameworks, NMC is modeling and emulation of the bionic brain for machine intelligence-promises to realize artificial intelligence while reducing the energy requirements of computing platforms [8]. NMC mimics neuro-biological architectures by VLSI systems containing electronic analog circuits, which aiming at brain-like capabilities and efficiencies.

Spiking Neural Networks (SNN) is also known as the third generation of neural network models, which increases the level of realism in a neural emulation. Spiking neurons model includes Hodgkin-Huxley, Leaky Integrate and Fire (LIF), Spike Response Model (SRM) and Izhikevich etc. Besides neuronal and synaptic state, SNN also incorporated the concept of time into their operating model. The SNNs exploit spatio-temporal information based on sparse and dynamic spiking event, and have advantage of low-power computing. The spiking neurons have a discontinuous activation function, and emit discrete spikes that are nondifferentiable; hence it cannot use directly the gradient-descent BackPropagation (BP) algorithm to training SNNs. Currently, the existing training methods for SNNs fall into three types: (1) unsupervised learning, such as spike-timing-dependent plasticity (STDP), Hebbian learning; (2) supervised learning, such as SpikeProp, Remote Supervised Method (ReSuMe), FreqProp, ANN-to-SNN conversion, Spatio-Temporal BackPropagation (STBP) [9] and Quantum Superposition SNN (QS-SNN) [10]; (3) reinforcement learning, such as Spiking Actor-Critic(SAC) method, reinforcement learning through reward-modulated STDP.

At present, BMI has achieved remarkable achievements in the brain-like neuronorphic technology. A large number of 'Big Brain' chips and systems have been designed, such as NeuroGrid [11], BrainScaleS [12], SpiNNaker [13], Darwin NPU [14], Tianjic [15], TrueNorth [16], Memristor, TPU [17], Loihi, DianNao [18] family, DishBrain [19], and DeepSouth [20]. In addition, synaptic efficacy and synaptic plasticity can be accomplished using emerging non-volatile memristive technologies such as resistive random-access memory (RRAM), phase-change memory (PCM), floating-gate transistor, and memristive dot products. Furthermore, the much brain-inspired software system has been developed, such as SpikeNET, NEURON, GENESIS, BRAIN and NEST emulator etc. Compass is a multi-threaded; massively parallel functional emulator and a parallel compiler that mapping a network of Long Distance Pathways (LDP) in the brain to TrueNorth [21]. Literature [22] present neuron models of the brain as Spaun (semantic pointer architecture unified network) for Nengo, which can emulate the human tasks, such as image recognition, serial working memory, reinforcement learning, counting, question answering, rapid variable creation, and fluid reasoning.

However, as a key technology of BLC, NMT needs to be studied on the basis of understanding the structure and neural mechanism of the brain. Before the mechanism of neural system is not completely clear,

it is very difficult to realize NMT in algorithm principle and model design. NMT inspired by the brain promise fundamentally different ways to process information with extreme energy efficiency and the ability to handle the avalanche of unstructured and noisy data. So brain-inspired computing needs a master plan [23].

D. Deep Learning

Deep learning, also known as feature learning, benefits from the combination of big data and high-performance computing. The development of deep learning has gone through four stages: (1) McCulloch and Pitts put forward a neuron model for logic and computation in 1943, which created the first Computational Theory of Mind and Brain (CTMB) [24]; (2) Rosenblatt proposed perceptron for linear classification in 1958; (3) Multi-layer perceptron (MLP) based on BP algorithm is used to solve nonlinear problems; (4) Hinton proposed deep learning in 2006.

In essence, deep learning is also a classic neural computing of structuralist technology. Combined with the traditional machine learning algorithms of functionalist and behaviorist, it can effectively solve the problems of high energy consumption and low intelligence of the existing computing system. For example, AlphaGo improved the performance of the Go program with CNN, reinforcement learning, and Monte Carlo tree search algorithm [25],[26] It is mathematically equivalent to using an MLP after the convolutional layers. With the application of deep learning in engineering systems, cognitive mechanisms such as perception, attention, memory and emotion are widely used in the intelligent processing of multimedia such as image, video, audio and natural language. The more and more novel Deep Neural Network (DNN) were designed, such as Forward-Forward (FF) algorithm and capsule network [27], Generative Adversarial Network (GAN) [28]. For example, it can greatly improve the performance of machine translation and intelligent retrieval in natural language processing by the employed Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) [29], DeepFair [30], Encoder-Decoder model, Transformer [31] and GPT-3 model with 175 billion parameters [32]. DNN is also a graph model in nature. Inspired by the great success of deep learning in machine learning tasks which are typically represented in the Euclidean space, Graph Neural Network (GNN) [33] is also introduced to solve the learning task of non-Euclidean domains.

However, as the most popular technology of BIC, deep learning is a black box model that lacks explainability. There are also technical bottlenecks in small samples and energy consumption, and it cannot be applied in the environment with high security requirements.

III. Scientific Theory Based on Brain and Mind Inspired Intelligence

For the study of brain and mind, semantic computing is a complex scientific problem in a visual or auditory scene. It has an essential enlighten to realize semantic computing of target recognition, and multimedia intelligent processing that the function, structure and social behavior of the cognitive framework and the neural mechanism. With the rapid engineering development of deep learning and cognitive computing in the field of artificial intelligence, more and more heuristic algorithms based on biological intelligence have emerged. However, there are essentially different from scientific theory research, technical route and method, and implementation of engineering and system among neuroscience, cognitive science and computing science. In order to solve the complex problem of audio-visual semantic computation, the computational model is established urgently for mimicking the brain and mind, inspired by the framework of cognitive function and the mechanism of neural processing.

A. Definition of Related Concepts of Brain and Mind Inspired Intelligence

Currently, there are two research directions which have attracted much attention in BMI. One is the Brain Inspired Computing (BIC) method based on systematic behavior to simulate cognitive function, the other is the Brain Like Computing (BLC) method based on neuron, synapse or local network structure to emulate neural mechanism. Considering that brain inspired intelligence, BIC and BLC have no exact definitions at present, these terms may be confused with each other. This section explains their differences and strictly defines the concepts related to Brain and Mind inspired Intelligence Theory (BMI Theory).

Definition 1 (BII Theory). Brain Inspired Intelligence (BII) is an intelligent model, method and system that enlightened human brain and realizes brain inspired intelligence information processing.

Definition 2 (BIC Technology). Brain Inspired Computing (BIC), also known as mind inspired computing, is a computing method inspired by the principles of cognitive mechanisms and mental functions, which simulates mental models from the functional level, and explores and designs mind inspird intelligence algorithms.`

Definition 3 (BLC Technology). Brain Like Computing (BLC) is a network architecture that emulates the brain nervous system. It focuses on the emulation of the nervous system at the system structure level, and explores and designs brain like intelligence algorithms.

Definition 4 (BMI Theory). Brain and Mind inspired Intelligence (BMI) is an innovative bio-inspired computing intelligent scientific theory, intelligent technology and intelligent engineering based on bionics. The inspiration for establishing BMI theory comes from functional architecture of cognitive system, structural mechanism of nervous system, and complex behavior of natural system.

Definition 5 (BMC Technology). Brain and Mind inspired Computing (BMC) is a intelligent model, intelligent algorithm and intelligent system that mimicking brain structure, mind functional and human behavior at the same time. BMC researches intelligent theoretical model and algorithm of perceptual computing and cognitive computing, and realizes new generation brain inspired and mind like intelligent system.

BMC focuses on the structural simulation of nervous system, the functional emulation of cognitive system and the behavior imitation of natural intelligent system, so as to solve the compatibility of functional emulation and structural simulation of intelligent computing. Firstly, BMC emulates the network structure of nervous system and brain information processing architecture. Secondly, BMC simulates the functional principle and mental information processing model of cognitive system, Thirdly, BMC imitates the complex system behavior of natural intelligence.

Aiming at the unstructured and complex semantic processing of multimedia computing, we propose a multimedia neural cognitive computing model.

Definition 6 (MNCC Model). Multimedia Neural Cognitive Computing (MNCC) is to construct multimedia information processing model and algorithm for the purpose to solve the problems of semantic processing of unstructured, massive, multi-modal, and temporal-spatial distribution in multimedia information. MNCC is a BMC model, which establishes a new generation of the multimedia information processing model and algorithms with cognitive computing of system behavior in macroscopic level, and neural computing of physiological mechanisms in microscopic level.

MNCC focuses on the perceptual computation and semantic cognitive processing of multimedia interactive information, especially on the feature extraction, content analysis and semantic computation

of visual media, auditory media, natural language and other media information. MNCC is a BMI model for multimedia intelligent processing based on the structure and mechanism of the nervous system, and the function and framework of the cognitive system.

In order to realize cross-modal content processing and solve the audio-visual cross-media computing problem, we further propose a cross-modal cognitive neural computing framework.

Definition 7 (CCNC Framework). Cross-modal Cognitive Neural Computing (CCNC) is cross-modal information processing framework and mind inspired cognitive computing method of cross-media knowledge reasoning based on MNCC model. CCNC is a BMC framework, which mainly solves the problems of cross-modal semantic computing by the mechanism of multisensory integration and multimodal cooperative cognitive.

CCNC focuses on the information fusion of different perception media, and multimedia semantic correlation. It usually explores cross-media computing methods based on temporal and spatial correlation. To overcome the bottleneck of cross-modal semantic computing, CCNC researches hierarchical framework and algorithm based on mind-inspired cognitive computing and brain-inspired deep learning.

Aiming at the problems of cross-modal target recognition in remote sensing intelligent information extraction platform, and cross-media semantic recognition in unmanned autonomous system, we further propose a cross-modal neural cognitive computing architecture.

Definition 8 (CNCC Architecture). Cross-modal Neural Cognitive Computing (CNCC) is a kind of system architecture of brain inspired cross-modal intelligence. On the basis of MNCC model and CCNC framework, CNCC adopts transfer learning, multi-modal cooperative cognitive mechanism of neural information and modal mutual information to design the information processing system architecture of cross-modal brain inspired intelligence at the level of cognitive computing, so as to solve the complex engineering application problems of cross-modal semantic computing and transfer learning.

CNCC architecture focuses on system engineering implementation of the media semantics cognition and cross-modal correlation. CNCC can be applied to cross-modal target recognition with different modal perception information, such as visible light, infrared, radar, sonar, etc.

B. Structure and Mechanism of the Nervous System

It are the source of bionic inspiration for the study of BMI theory that the structure and mechanism of the nervous system, and function and the framework of the cognitive system. There is a systematic study of the brain's information processing mechanism in different disciplines. On the one hand, the neuroscience analysis brain mechanism of neural processing at the levels of the cortical structure and the neural circuits based on the white box method. On the other hand, cognitive science research model of mind's information processing through cognitive function and the phenomenon based on the black box method. However, artificial intelligence of computer science realizes logic computation of a finite state machine based on Turing machine and Von Neumann architecture. Although computer science has made great advances, the principle, structure and function of brain, mind and computer are essentially different.

Behind the neurodynamic characteristics of brain structure and the emergence of social behavior of mental function, there are the basic laws of complex intelligent system. Generally, the neocortex of the cerebellum is the core component of intelligent processing in the field of neurocognitive science; the thalamus is the switch of information entry and selective attention; the limbic system and the hippocampus are the controllers for memory and emotion. The human central nervous system is composed of white matter and grey matter, and has

the obvious symmetry and contralateral. The neocortex structure of the gray matter is similar to the digital-analog electronic processing unit with processing linear and nonlinear function. The LDP of the white matter made up the complex White Matter Network (WMN). It can be regarded as wiring diagram of neural processing. So the neocortex structure and WMN are very important for understanding the overall structure of the brain. The research on the computable model of nervous system includes Cortical Model (see Appendix A), LDPs and Neural Circuits (see Appendix B). Among them, Hierarchical Temporal Memory(HTM) [34] is very noteworthy (see Appendix C).

Fig. 1 is our WMN visualization of 48 brain regions form the high accuracy human brain LDP database in documents [35],[36], which consider WMN connection weights and nodes size. The analysis found that there were a large number of long-distance loops in the human brain WMN, and there were also a large number of connections between the thalamus and cortex. So the relay nuclei of the thalamus are a controller of the selective attention to sensory information, and the association nuclei of the thalamus are a switch of cortical processing information.
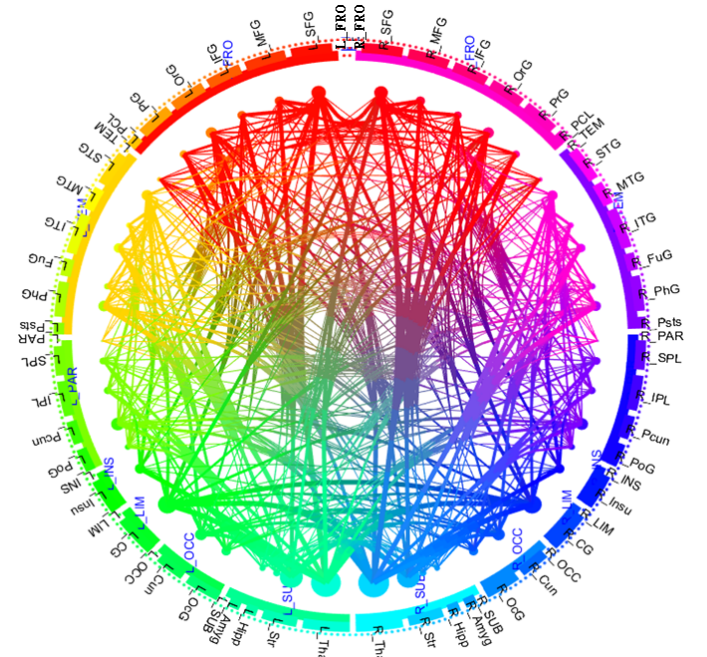

Fig. 1. WMN structures with connection weights visualization on 48 brain regions.

The hierarchy of cortical function and structure of neural pathways and circuits can provide significant evidence for the neural cognitive model. Neural circuits are the important material of relevance such as feedback, stochastic resonance, recurrence iterative, resonance, memory, emotion, attention, language, and thinking. It can inspire for build neural model that the hierarchical structure of cortical function, and the structure between the neural pathways and loops. Studies indicate that the central nervous system is a scale-free and small-world complex network. On the basis of the WMN visualization and document [37],[38], we propose a simplified structure model of the whole brain WMN in Fig. 2.

C. Function and Architecture of the Cognitive System

Generally, the human's mind activities involve many aspects in cognitive neuroscience. Specifically, it includes sensation (such as light, sound, touch, taste, smell, etc.), perception (such as seeing, hearing, feel, tasting, smelling, etc.), behavior (such as movement, reaction, choice, interaction, etc.), and cognition (such as attention, memory, emotion, logic, language, reasoning, understanding, problem-
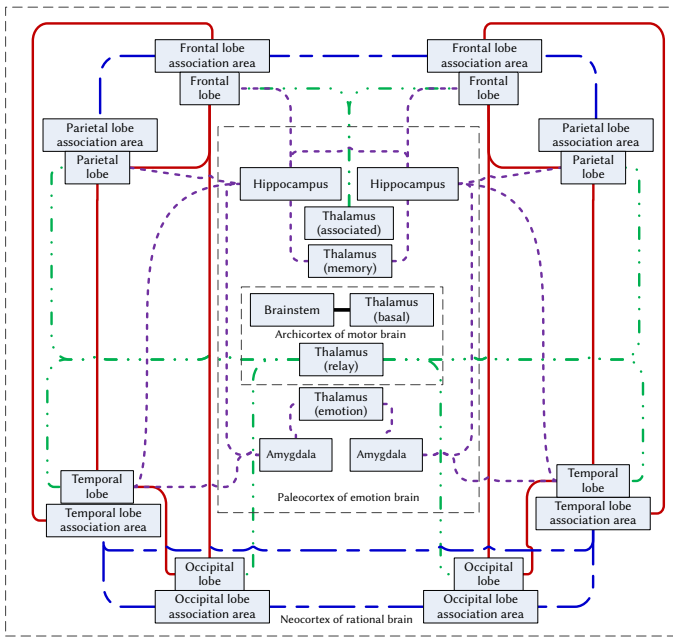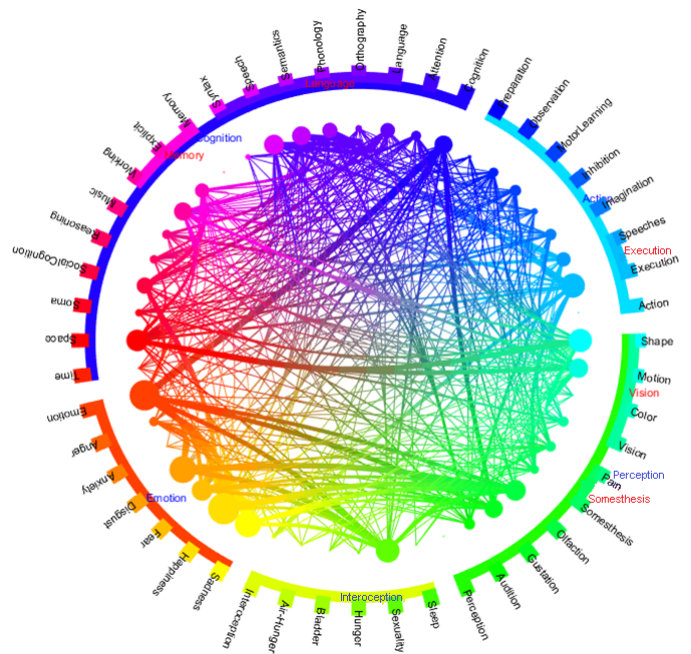
Fig. 2. The WMN structure model.

Fig. 3. Visualized analysis of 48 cognitive functions.

solving, planning, etc.). Cognitive science explores and studies the human thinking mechanism, especially the processing mechanism, by constructing cognitive models. It also provides a new architecture and technology for the design of intelligent systems.

In cognitive psychology, there are many cognitive frameworks such as ACT-R (Adaptive Control of Thought-Rational), SOAR (State, Operator And Result), ART (Adaptive Resonance Theory), synesthesia model, elementary perceiver and memorizer semantic network, human associative memory, GPS (General Problem Solver), PDP (Parallel Distributed Processing) and agent model. Among them, cognitive theory based on Bayesian probabilistic (see Appendix D) and perception, memory, and judgment mode [39] are very valuable cognitive architectures (see Appendix E). The computational theory based on the cognitive architecture can establish a cross-modal computing model of audio-visual media (see Appendix F).

Functional neuroimaging is an internal reflection of cognitive function, and it also is a technique for studying the cognition mechanism of the mind. Fig. 3 shows the results of our visual analysis of 48 cognitive functions in the neuroimaging database BrainMap (http://www.brainmap.org/taxonomy). BrainMap is a neuroimaging database of coordinate based functions and structures of the literature [40]-[42]. In general, the cognitive function of the human mind can be clearly found in the hierarchical structure.

Based on the visualization of cognitive function and the analysis, we proposed a framework for mind cognitive function (Fig. 4). Here, the cognitive process is mainly composed of perception pathway, motion controlled pathway, attentional controlled pathway, memory and emotion circuit, feeling and decision circuit,and judgment and control circuit etc.

D. ComputableTheoretical Hypothesis of Brain and Mind

Fig. 5 is our visualized analysis of the correlation between 48 brain regions and 48 cognitive functions in the human brain LDP database according to the literature [35],[36] In order to find the inherent law of neurocognitive, Fig. 6 is our simplification visualization of the correlation between 14 brain areas (includes 7 left brain areas and 7 right brain areas) and 5 cognitive functions in the literature [43],[44]. It can be noted that it is essentially fully connected between the cognitive function and neural connections. Frontal lobe and basal ganglion are
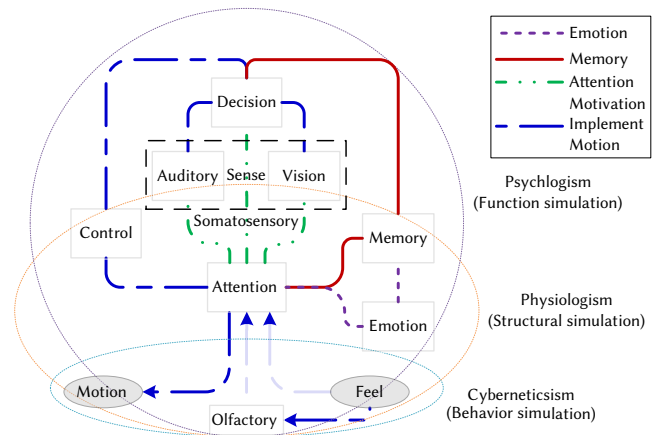

Fig. 4. Cognitive framework of mind.

the centers of neural processing, and the perception and emotional are the core of cognitive function. Cognitive function is closely related to the frontal temporal lobe, the thalamus and basal ganglion are closely related to the emotion, which is the projection center of information. These results are consistent with the basic theories of neuroscience and cognitive science.

The relationship between the structure of nervous system and the function of cognitive system is complex system of information control, and the relationship is unity of opposites. On the one hand, neural structure determines cognitive function; on the other hand, cognitive function also restricts neural structure. Both determine the system's intelligent behavior.

We can think that the structure of the brain nervous system and the function of the mental cognitive system constitute the "hardware" and "software" of the agent respectively, and the intelligent behavior of agents is generated by computational process. Fig. 7 shows the corresponding relationship among neural structure, cognitive function and intelligent behavior of the WMN in brain and mind. It is an isomorphic mapping between the brain structure of nervous system and mind function of cognitive system. Both of them reflected the different perspectives of the intelligent behavior.
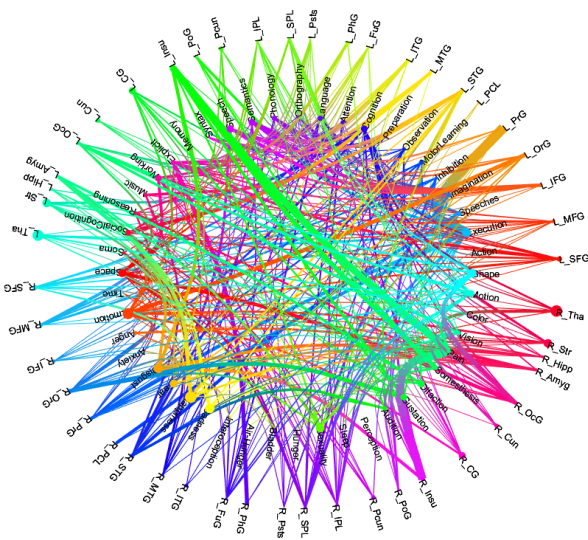
Fig. 5. Visualization and analysis between 48 brain regions and 48 cognitive functions.
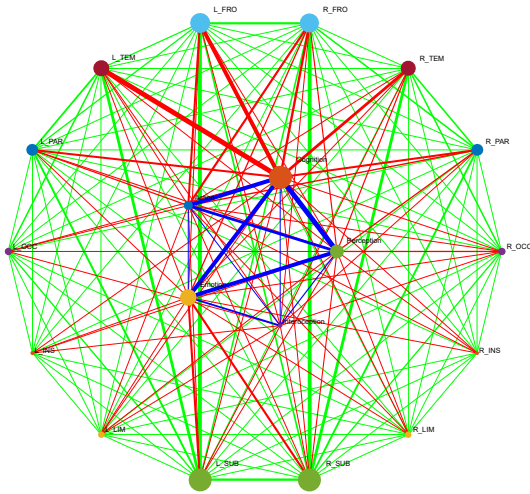

Fig. 6. Simplification visualization between 14 brain areas and 5 cognitive functions.
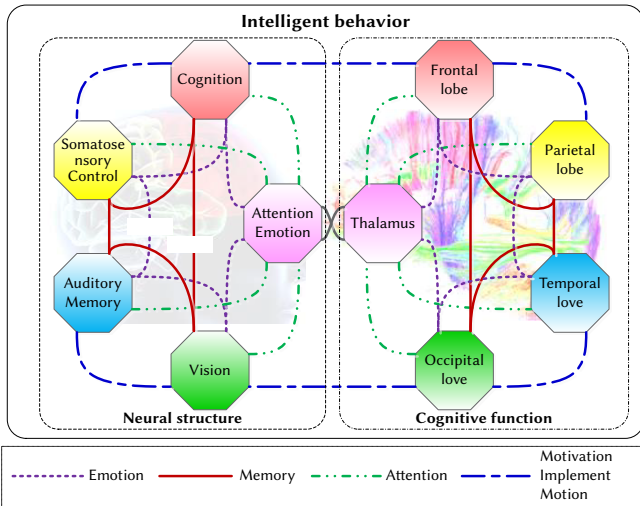

Fig. 7. The relationship among neural structure, cognitive function, and intelligent behavior.

According to the bionic principle and mechanistic, and based on the relationship between the structure, function, behavior and environment of natural intelligence, we proposes the following Cognitive Function and Information Hypothesis (CFI Hypothesis), Neural Structure and Control Hypothesis (NSC Hypothesis), and Complex System and Behavior Hypothesis (CSB Hypothesis) based on Function-Behavior-Structure(FBS) model [45] and SCI theory (system theory, cybernetics theory and information theory).

Hypothesis 1 (CFI Hypothesis). The mind function M comes from the organic combination of the modes of the cognitive system Ψ. As shown in Equation (1), cognitive function is produced by the orderly information processing by the system, which is an entropy reduction process (minimization of information entropy). Cognitive system can explore the function and processing mechanism of intelligence on a macroscopic level based on information theory.

$$M_i = \bigcup \left(\Psi_i | \sum F_k \right)$$
$$s.t. \quad argmin_F(-\sum p(f_k) \log p(f_k)) \tag{1}$$

Hypothesis 2 (NSC Hypothesis). The brain architecture B depends on the network structure of nervous system N. As shown in Equation (2), the dynamic optimization and control strategy of nervous system structure S is the result of multiple iterations and joint actions of target expectation Te, feedback information Fi and environmental interaction Ev. The nervous system can study the structure and control principle of intelligence on a microscopic level based on cybernetics.

$$B_i = \bigcap \left(N_i | \prod S_k \right)$$
$$s.t. \quad S_k \leftarrow Policy(S_{k-1}, Ev, Fi, Te) \tag{2}$$

Hypothesis 3 (CSB Hypothesis). Intelligent system is a complex nonlinear system with hierarchy. As shown in Equation (3), the intelligent behavior H is a process in which the module T processes the perceptual information layer by layer to realize the convex optimization computation C. Intelligent system can research the behavior and computational process of intelligence in mesoscopic level based on system theory.

$$H_i = C_i \left(C_{i-1} \left(\cdots C_1(T_1) \right) \right)$$
$$s.t. \quad C_i \in Convex\ function \tag{3}$$

According to the relationship between intelligent behavior, brain structure and mind function, Brain and Mind inspired Intelligence Hypothesis (BMI Hypothesis) can be proposed as follows.

Hypothesis 4 (BMI Hypothesis). Assuming that the nervous system N in brain B has structural S, the cognitive system Ψ in mind M has functional F, the natural system I has complex behavior H, and the computational model C has information processing process P, there is a homomorphic mapping Γ to realize brain and mind inspired intelligence (Equation 4).

$$\Gamma : \left\langle B \left(\bigcup (S|N) \right), M \left(\bigcap (F|\Psi) \right) \right\rangle \rightarrow I \left(\sum H \right) \Big| C \left(\prod P \right)$$
$$s.t. \quad \begin{cases} \{S,N,B\} \cong \{F,\Psi,M\}, \{C,P\} \sim \{I,H\}, \\ \Psi \cap N = \varnothing, \Psi \subset M, N \subset B, I \subset C. \end{cases} \tag{4}$$

IV. Key Technologies and Engineering Applications of Brain and Mind Inspired Computing

A. Semantic-Oriented MNCC Model

In view of the similarity neocortical structures and cooperation of cognitive function, we propose the following Brain and Mind Mechanism Hypothesis (BMM Hypothesis) and Target Classification and Recognition Hypothesis (TCR Hypothesis).

Hypothesis 5 (BMM Hypothesis). It can be assumed that the

information processing mechanism of the neocortex is universal in the brain areas. The audio-visual and other sensory procession can be modeled by uniform cortical function, and it can be applied to prediction, learning, reasoning and other general problem solver.

Hypothesis 6 (TCR Hypothesis). It can realize that the object semantics computing by BMC methods. That is, it needs to emulate the hierarchical processing, and attention mechanism of the nervous system in low-level. It also needs to imitate the framework of memory and emotion in middle-level, and simulate the function of probabilistic and causality reasoning based on the cognitive framework and integrated in high-level.

It is very necessary to establish unified hierarchical theory in mechanism of integrating behaviorism (or actionism), functionalism (or symbolism) and structuralism (or connectionism) [46] Therefore, we constructed 4 layers Multimedia Neural Cognitive Computing (MNCC) model for semantics-oriented computing of BMI. Each of the layers is described as follows:

- Layer 0 (Hybrid computation layer based on mathematical model of endocrine, immune and neurochemical).

  The hybrid computation layer emulates biochemical brain intelligent by Artificial Endocrine System (AES), Artificial Immune System (AIS) and NeuroChemical System (NCS) such as necrohormones, neurotransmitter and neuromodulator (or neuropeptide).

- Layer 1 (Perceptual computation layer based on control models).

  The perceptual computation layer bionics realizes the cognitive function of perception and attention, which formed by the neural structure of thalamus, primary cortex of temporal lobe, parietal lobe and occipital lobe. The perceptual computation layer imitates motor brain intelligent of perceived behavioral control on archicortex.

- Layer 2 (Neural computation layer based on structural models).

  The neural computation layer bionics realizes the cognitive function of memory, emotion and sensation, which formed by the neural structure of thalamus, secondary cortex of temporal lobe, parietal lobe and occipital lobe. The neural computation layer imitates emotional brain attention circuit, emotional circuit and memory circuit of the limbic system on paleocortex. The models of this layer had incremental learning based on emotion computing, reinforcement learning based on memory, deep learning such as SNN, DBN and CNN et. al.

- Layer 3 (Cognitive computation layer based on functional models).

  The cognitive computation layer bionics realizes the cognitive function of perception, inference, prediction and judgment, which formed by the neural structure of frontal lobe, association cortex of temporal lobe, parietal lobe and occipital lobe. The cognitive computation layer simulates rational brain of hierarchical ensemble learning, subjective Bayesian cognitive learning, language, and thinking control in neocortex. The models of this layer had HMM, LDA, PGM et. al.

Semantic-oriented computing needs to research and discover the cortex structure of the nervous system, the network structure of the white matter, and the cognition function of the mind, such as hierarchical processing, incremental memory, emotional reinforcement, probability ensemble and so on.

As Fig. 8 shows, a semantic-oriented MNCC model based on the neural structure and cognitive framework were proposed. MNCC model is designed based on the characteristics of neural cognitive information processing such as information transmission and feedback, hierarchical, distributed and parallel processing. It extracts semantic information from the representation media by multiple steps such as a region of interest (ROI) extraction, saliency target detection, object-oriented incremental recognition, multi-scale target reinforcement, hierarchical ensemble process and other steps.

B. Hierarchical CCNC Framework

In view of the hierarchical of the natural media such as audio and video, high-level features can be achieved through the combination of low-level features. There are hierarchical structures in the language text such as words, sentences, paragraphs, and documents. There are hierarchical structures in a speech sound, for instance, sampling, phonemes, syllables, and words. Similarly, there are hierarchical structures in the natural images, for example, pixels, edges, shapes, textures, objects and scenes. From the related research of cognitive science and neuroscience, the information processing of cognitive function and neural structure also has a similar hierarchical structure. Considering the hierarchy of neural cognitive for semantic computing, Fig. 9 is our further improved hierarchical CCNC framework based on MNCC.

The hierarchical CCNC framework is designed based on the Brain and Mind inspired Computing Hypothesis (BMC Hypothesis) as follows.

Hypothesis 7 (BMC Hypothesis): The computing system can be layered in hybrid computation, perceptual computation, neural computation, and cognitive computation to realize general artificial intelligence. That is, it can emulate low-layer perception computing process based on saliency mechanism and swarm intelligence. It can imitate the middle-layer of hierarchical feature computing process based on deep learning, reinforcement learning, and incremental learning. It also can simulate high-layer hierarchical decision process based on probability reasoning, causality reasoning, and ensemble learning.

The goal of CCNC mainly solves the problems of multimodal semantic and cross-modal computing. Based on the 4 layers of the MNCC model, the CCNC framework extends it into 7 sub-layers and 1 hybrid layer, which can realize the semantic computing function. Each layer is described as follows:

L_0 **Hybrid computation layer**

This layer is designed and implements the dynamic I/O regulation according to the prior rules and inhibition and excitation mechanism of AES and AIS. It can also inhibit or excite to other layers by NCS.

L_1 **Perceptual computation layer**

$L_{1.1}$ This sub-layer realizes pre-processing of perceptual information.

$L_{1.2}$ This sub-layer imitates attention mechanism of the thalamus-cortical circuit and extracts the saliency features from the media target based on sparse representation.

L_2 **Neural computation layer**

$L_{2.1}$ This sub-layer emulates the hierarchical structure of cortical columns, and constructs the semantic classifier based on deep learning.

$L_{2.2}$ This sub-layer emulates the emotional reward and punishment mechanism of the limbic system, and realizes the function of the semantic reinforcement learning.

$L_{2.3}$ This sub-layer emulates the memory mechanism of the cortex-hippocampus system and realizes the function of the incremental semantic learning.

L_3 **Cognitive computation layer**

$L_{3.1}$ This sub-layer simulate the theory of mono-modal cortical column and Bayes subjective probability to realize semantic cognition computing.

$L_{3.2}$ This sub-layer simulate the information integration multi-modal cortical column to realize semantic ensemble learning of multiple classifiers.

TABLE I. The Symbol of CCNC Framework and Its Implication

Symbol	Types	Implication
MM	Multidimensional matrix set	Media set(include image, audio, text, and video)
Ma	Tensor	Media data
SC	Algorithm	Saliency computation
Sa	Sparse tensor	Temporal saliency feature (sparse representation)
Sv	Sparse tensor	Spatial saliency feature (sparse representation)
DL	Algorithm	Deep learning algorithm
IL	Algorithm	Incremental learning algorithm
RL	Algorithm	Reinforcement learning algorithm
EL	Algorithm	Ensemble learning algorithm
CC	Algorithm	Cognitive computing algorithm
Cp	Set	Target semantics
Ct	Vector	Features of temporal perception (probability topic)
Cs	Vector	Features of spatial perception (probability topic)
Fa	Sparse matrix	Features of temporal senses (probability distribution)
Fv	Sparse matrix	Features of spatial senses (probability distribution)
Ma	Sparse matrix	Time increment of DNN
Mv	Sparse matrix	Space increment of DNN
Mt	Vector	Time increment of cognitive topic
Ms	Vector	Space increment of cognitive topic
Mp	Vector	Feedback information of incremental learning
Mn	Vector	Attention increment of saliency computation
Es	Parameter	Reinforcement feedback of saliency computation
Ei	Parameter	Incremental feedback of memory
EH	Set	Endocrine molecules which effect on input and output
SS	Set	Semantic state of chemical solution
TS	Mapping	Reaction rule

The hierarchical CCNC framework can be described by following the 7-tuple <SC, EL, IL, RL, DL, CC, EH>. It is mapping processing that the CCNC framework training and recognition, which can be described following Equation (5).

$$CCNC: \langle MM | MNCC \rangle \to Cp$$
$$s.t. \quad CCNC = \langle SC, EL, IL, RL, DL, CC, EH \rangle \quad (5)$$

The symbols and illustration of the hierarchical CCNC framework in Fig. 9 and Formula 5 are shown in Table I.

The formal semantics of CCNC framework based on CHemical Abstract Machine (CHAM) presented in Appendix G. The algorithms description for semantic learning and recognition of hierarchical CCNC framework presented in Appendix H.

C. System Applications of CNCC Architecture

A wide range of applications of semantic-oriented MNCC model and hierarchical CCNC framework would be identified such as unmanned autonomous system and search engines of cross-media intelligent [53]. It would have profound significance for the exploration and the realization of the BMC. With the development of software defining satellite, on-board software urgently needs high productivity computing to solve the problem of remote sensing intelligent information extraction.

We established a Cross-modal Neural Cognitive Computing (CNCC) architecture based on MNCC model and CCNC framework. CNCC can provide high productivity intelligent algorithms and toolkits for remote sensing information extraction. As Fig. 10 shows, CNCC architecture had been applied to the algorithms of scene classification, target detection and target recognition of high-resolution remote sensing images [51].

V. Discussion

In order to verify the application performance based on BMC in remote sensing information extraction. Table II lists the experimental results of our previous research on scene classification, target detection and target recognition based on the CNCC architecture.

TABLE II. The Experimental Results Sematic Recognition Based on CNCC Architecture.

Sematic recognition	Datasets	Model / Method	AP (%)	OA (%)	PD (%)	FAR (%)	MDR (%)
Scene classification [47]	HRSS	MNCC/ SC-MNCC	84.73				
Scene classification [47]	UCMLU	MNCC/ SC-MNCC	88.26				
Sonar target classification [48]	SITC	CCNC/ SABP	91.11				
Target detection [49]	HRSHTD	MNCC/ SLS-CNN			95.00	8.00	5.00
Ship detection [50]	SAR	CCNC/ SD-SNN			91.63	9.48	11.02
Tank recognition [51]	MSTAR	CCNC/ TCR-EL-DHMM	99.90	99.88			
Target recognition [51]	HSTCR	CCNC/ TCR-IREL-OOMS	97.00	96.93			
Hyperspectral image classification [52]	IP	CCNC/ SABP	99.31	98.21			

The Average Precision (AP) of scene classification algorithm based on MNCC model is up to 84.73% on High-resolution Satellite Scene (HRSS) dataset of Wuhan University and reaches 88.26% on University of California Merced Land Use (UCMLU) dataset. For target detection algorithm based on MNCC model on High-resolution Remote Sensing Harbor Target Detection (HRSHTD) dataset, the average Probability of Detection (PD) is 91.63%, False Alarm Rate (FAR) is 8.37%, and Missed Detection Rate (MDR) is 9.35%.

The experimental results show that AP and Overall Accuracy (OA) of target classification algorithm based on CCNC framework are 96.93% and 97.00% on High-resolution Ship Target Classification and Recognition (HSTCR) dataset, respectively [51]. It also reaches 99.90% and 99.88% on Moving and Stationary Target Acquisition and
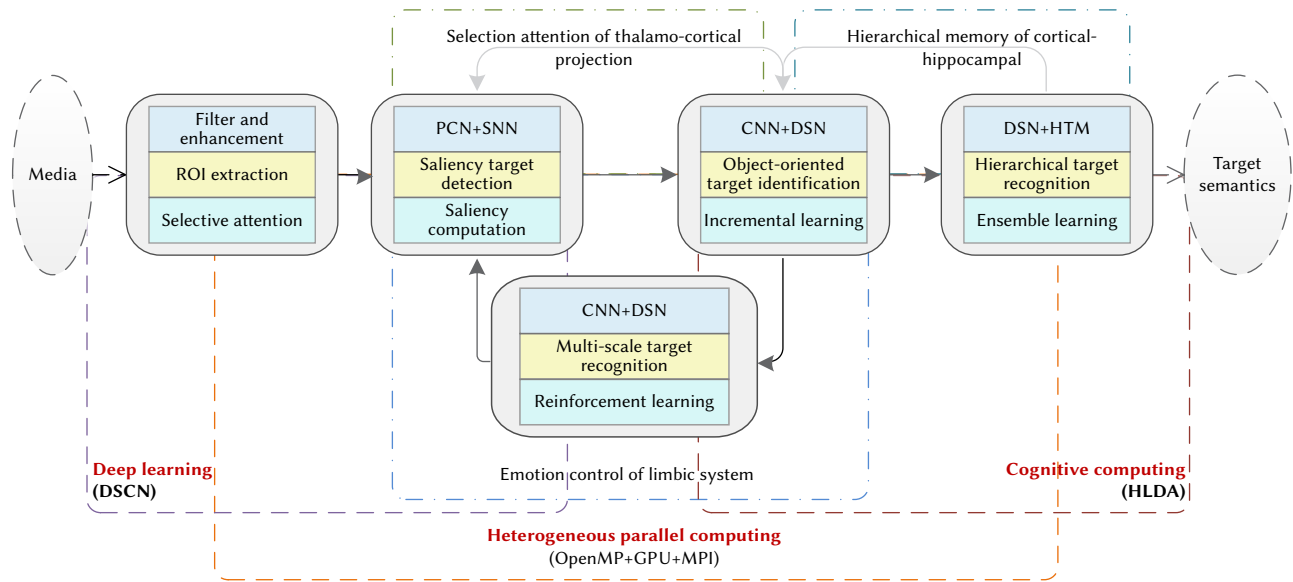
Fig. 8. The semantic-oriented MNCC model.
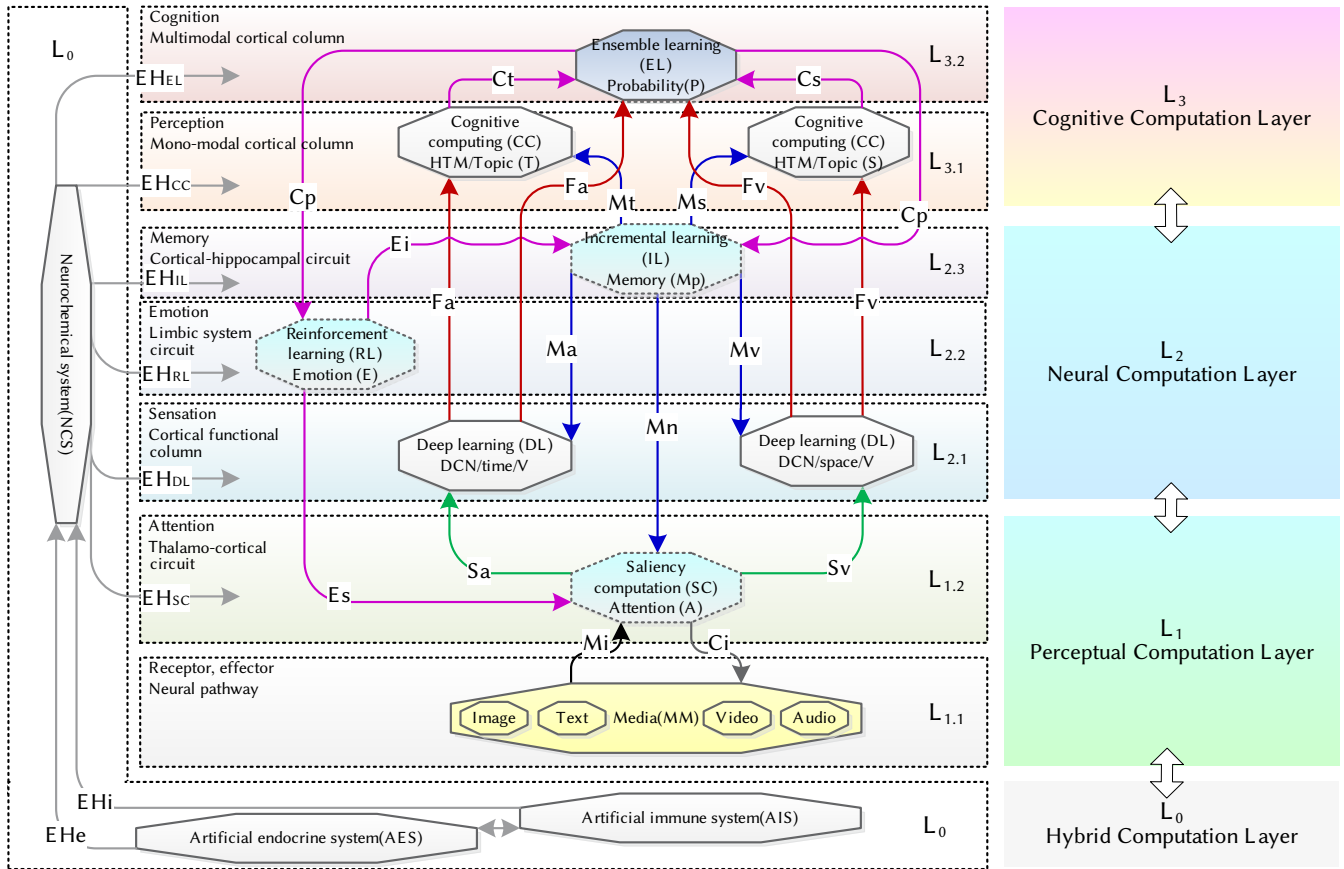
Fig. 9. The hierarchical CCNC framework.

Recognition (MSTAR) dataset, respectively. It shows that the CNCC architecture can address the problem of semantic learning on remote sensing image, which is complex ground objects.

This research shows that the semantic oriented MNCC model and the hierarchical CCNC framework designed by us based on brain mechanism and mind architecture can effectively improve the semantic processing performance of multimedia and cross-modal information, such as target detection, target classification and target recognition.

VI. Conclusion

To address the problems of scientific theory, common technology and engineering application of multimedia and multimodal information computing, we are focused on the theoretical model, algorithm framework and system architecture of BMI based on the structure mechanism simulation of nervous system, the function architecture emulation of cognitive system and the complex behavior imitation of natural system.
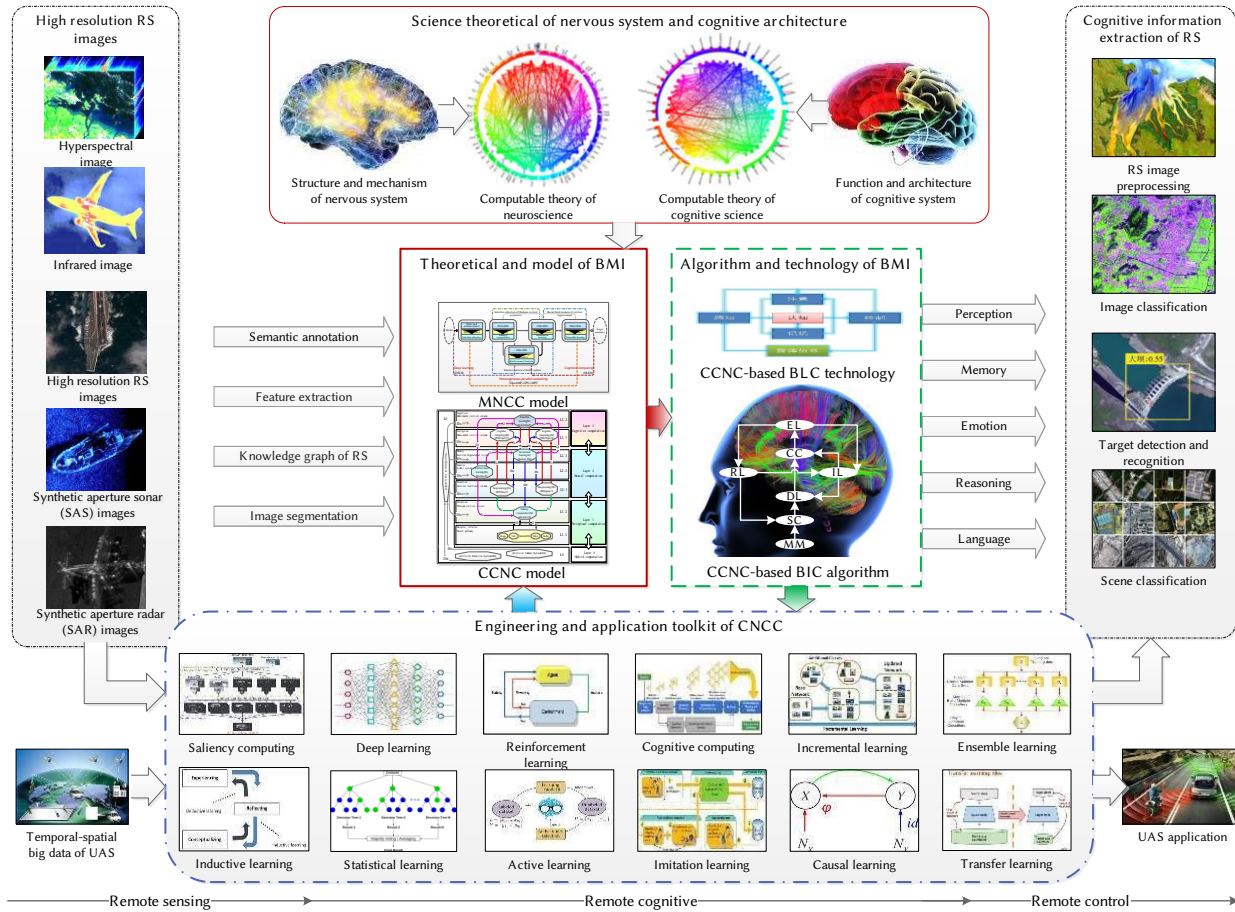
Fig. 10. The system application of the CNCC architecture for information extraction of remote sensing and target recognition of unmanned autonomous system.

Based on information theory, system theory, cybernetics and bionics, we define the concepts of BMC and propose the assumptions of BMI. Aiming at scientific problems of BMI modeling, the cortical models and nervous system structure in human brain WMN had been analyzed; the hierarchy characteristic of architecture and cognitive system function in mind had been explored. The relationship between nervous system and cognitive framework for BMI had also summarized. Then hierarchical CCNC framework is proposed based on the MNCC model, and the rationality of the hierarchical CCNC framework is formally analyzed based on CHAM. The semantic learning and recognition algorithm of our models are given. Our research on remote sensing intelligent information extraction and cross-media information retrieval shows that the scene classification, target detection, target classification and target recognition based on BMC algorithm have very high performance.

The BMI theory proposed can be widely used in high-resolution earth observation system and cross-media search engine and other applications. Looking to the future, CNCC architecture will be applied to more cross-modal intelligence information perception of unmanned autonomous systems and platforms, such as Unmanned Ground Vehicle (UGV), Unmanned Aerial Vehicle (UAV), Unmanned Surface Vehicle (USV), Unmanned Underwater Vehicle (UUV), Software Defined Satellite (SDS), intelligent robot and other unmanned autonomous equipment. The next step is to improve the BMI theoretical system, overcome the key technologies of BMC, and realize the state-of-the-art application of complex systems based on CNCC architecture.

Appendix

A. Cortical Model

There are three types of nervous system models: description model of nervous system, neural mechanism model, and interpretation model of neural function. The description model quantitatively describes nervous system based on the experimental data. The mechanism model emulates nervous system how to run. The interpretation model explores the basic principles of the nervous system, and the construction of the nervous system why so run. Typical nervous system models include neuron model, synaptic model, cortical model and structural model of the nervous system.

According to the evolutionary hypothesis of the triune brain [54], Paul MacLean divides the model of human brain structure and function into 3 specific regions: archicortex, paleocortex and neocortex. The archicortex originates from motor brain (reptilian), which cortical cortical structure is not very obvious. The paleocortex of the emotional brain (paleomammalian) lies in limbic system consists of 3 layers of neurons. The neocortex consists of 6 layers of neurons, which accounted for 90% of the area of the rational brain (neomammalian).

The triune brain hypothesis is a controversial and extremely simplified model [54], [55]. Generally, the neocortex can be divided into primary areas, secondary areas, association areas in function.

The layer structure of 3 types cortical areas [55], [56] as showed in Fig. 11. The research shows that 6 layers of the neocortex have different functions. For example, the L4 layer receives inputs information. The L2 and L3 layers make up a local circuit for information processing. The L1 layers achieve intersection and inhibition projection information of internal neurons, and information output from the L5 and L6 layers.
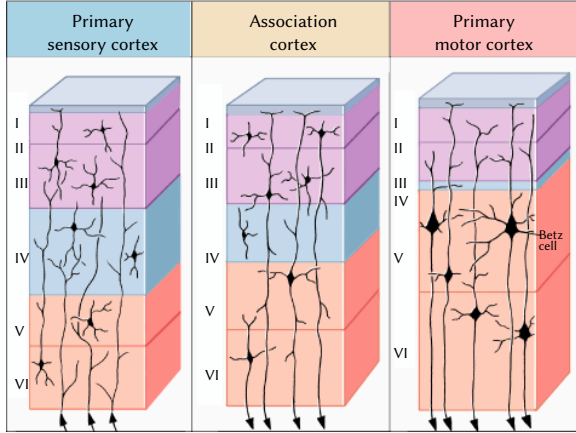
Fig. 11. Cortical structure.

Most studies suggest that neocortex has the similar structure in vision area, audition area, and association area. Cortical columns are a basic unit for information processing in neocortex. Cortical columns have the phenomenon of hierarchical processing and the mechanism of lateral inhibition of each other. Micro-columns consist of local circuits in neocortex. Physical stimuli are perceived and encoding to generate neural spiking coding by visual-auditory sensory neurons. The micro-column is feature detection, and macro-column or super-column makes up of micro-columns to process special information and generates some cognitive functions. The spiking probability is propagating among micro-columns. Micro-columns collect information from lower neighbor micro-columns and disseminate information from upper neighbor micro-columns [43]. At the same time, it also receives feedback information from LDP, and prediction information from an upper neighbor.

1. Temporal-Spatial Structure of Micro-Column Node

For simplicity in the model design, we firstly merge micro-column with 6 nodes (Fig. 12(a)) to micro-column with 3 nodes (Fig. 12(b)). The middle layer (L4) receives the input information. The lower layers (L5 and L6) send output information, and the upper layers (L1, L2, L3) process information. In fact, cortex information processing has the spatial-temporal property. So we further simplify the model structure with 2 nodes. It is noted that this simplification does not lose the advantage of bionics. For instance, the node is double structure in HTM, RBM, SVM and so on. As shown in Fig. 12(c), S mimicking functions from L1 to L4, and simulates memory and spatial patterns process [43]. T mimicking functions of L5 and L6, and simulates memory and temporal patterns process. Both nodes S and T memories belief which comes from owner and other nodes.

2. Hierarchical Network Architecture of Super-Column

According to neurocognitive system hierarchical architecture and temporal-spatial locality, super-column architecture also uses hierarchical, multi-level, and bidirectional mapping structure. Super-column composed by a micro-column with principles of "the same layer collaborative" and "hierarchical processing" (Fig. 13) [43].
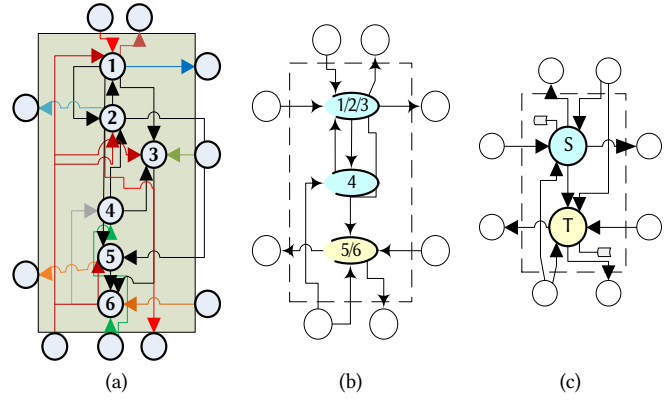
Fig. 12. The hierarchical structure model of the micro-column. (a) Micro-column structure with 6 nodes. (b) Micro-column structure with 3 nodes. (c) Micro-column structure with 2 nodes.
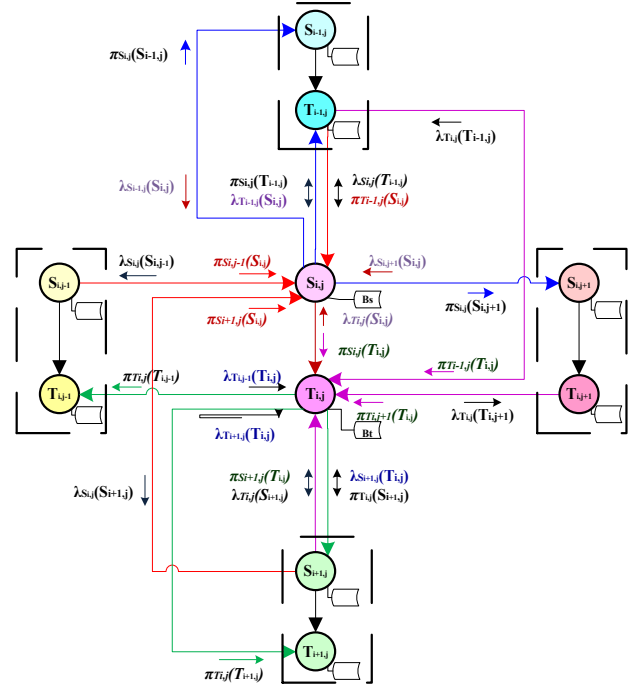
Fig. 13. The structure model of the super-column.

B. Long DistancePathways and Neural Circuits

According to the whole brain LDP database, the frontal lobe has the core nodes, and the thalamo-cortical projection system is the key connection in network structure of the human's brain. Both human visual system and human auditory system have a dual stream model: dorsal and ventral pathway, as shown in Fig. 14. "What" is happening in the dorsal pathway, and "where" is happening in the ventral pathway.
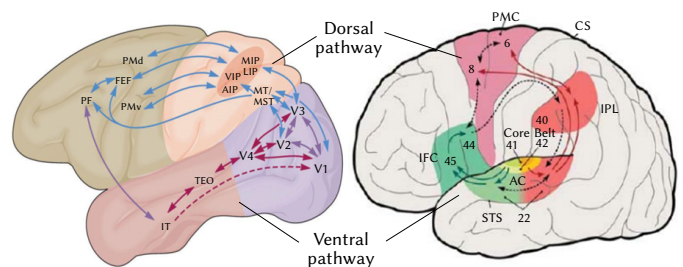
Fig. 14. The dorsal and ventral pathway in human visual system (left) and human auditory system (right).

The high accuracy human brain LDP database based on the experimental data taken from documents was constructed. Fig. 15 shows the pathways model in human visual system and human auditory system [35]-[38].
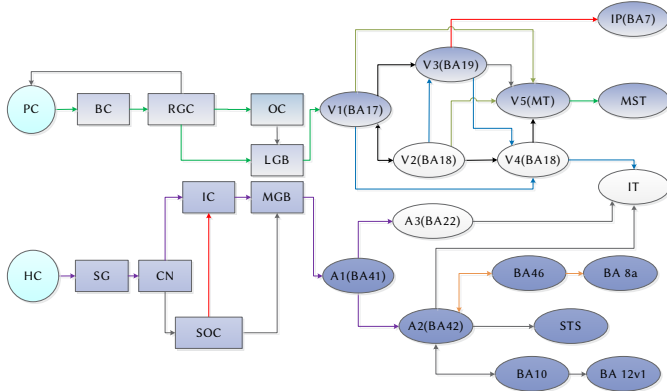
Fig. 15. The processing pathway model of human visual system (up) and human auditory system (down).

C. Hierarchical Temporal Memory

Hierarchical Temporal Memory (HTM) model [34] is a kind of neocortex structure and function by Jeff Hawkins and Dileep et al. It adopted Bayesian Belief Propagation (PBP) theory to explain the neocortex process of recognition and reconstruction (Fig. 16). In order to further simulate the structure of the neocortex, the concept of the cognitive domain of sparse distributed representation and other neuroscience concepts, such as the dendrites, synapses, and so on, is introduced. It proposed Cortical Learning Algorithm (CLA) in HTM, and its fundamental idea is hierarchy structure, and invariant representations of spatial patterns and temporal patterns and sequence memory.
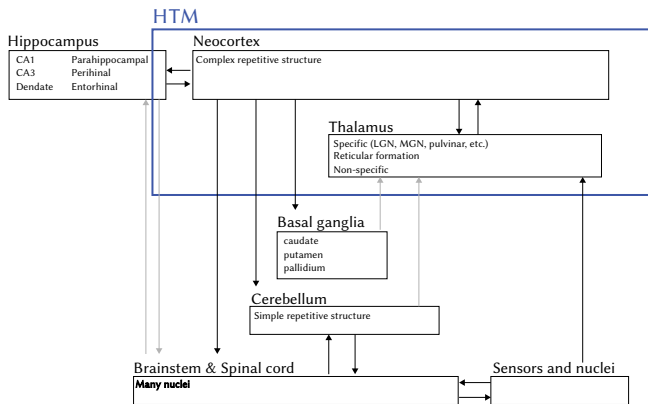
Fig. 16. HTM model.

D. Cognitive Theory Based on Bayesian Probabilistic

Since the Bayesian proposed the probabilistic theory in 1963, the probability reasoning and decision-making of the uncertainty information had become an important content of the researches on the objective probability and cognitive processing. Bayesian rule describes the likelihood between the priori probability (marginal probability) $P(x_i)$ and the posterior probability (conditional probability) of the historical information $P(x_i|x_j)$ The Bayesian rule provides a method for modifying and reasoning about the probability distribution of the subjective judgment $P(x_i)$ for observed phenomena. If x_i, x_j is condition independent, the sum-product rule can be can be derived by Bayesian inference as follows Equation (6).

$$\begin{cases} Sum \quad rule: P(x_j) = \sum_{i=1,2,...,n,i\neq j} P(x_j,x_i) \\ Product \quad rule: P(x_1,x_2,...,x_n) = \prod_{i=1}^{n} P(x_i|\pi(x_i)) \end{cases}$$
$$s.t. \quad P(x_i|x_j) = \frac{P(x_j|x_i)}{P(x_j)}P(x_i), P(x_ix_j) = P(x_i)P(x_j) \quad (6)$$

It is the mainstream method of machine learning and reasoning depending on the uncertainty representation of the probability, the Bayesian rule, and the extension model. Cognitive researchers use Bayesian brain model [57] to simulate the cognitive process and model of mind. It is investigated cognitive processing law of subjective probability estimation by a probability model. Bayesian brain theory believes that the brain is a predictive machine, and cognition is the process of probability calculation.

E. Perception, Memory and Judgment Model

Cognitive science researchers think that between the cognitive of the human mind and the computer information is similar in processing process. They are establishing cognitive computing theory according to computers to simulate human cognitive processes. It is research and analyses the processes and principles of human cognition, discover the main stages and pathways of cognitive processes, and establish the relationship between cognitive processes and computing workflow.
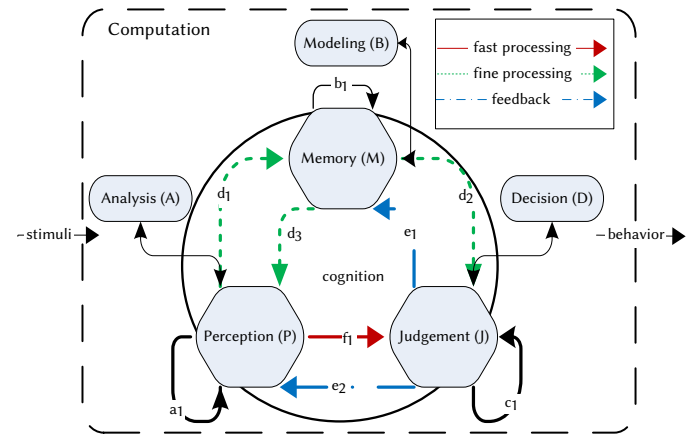
Fig. 17. PMJ model.

Fig. 17 is a cognitive computing model, which is constructed based on Perception, Memory and Judgment (PMJ) model from literature [39], [58]. Cognitive processing mainly consists of 3 stages which include perception (a_1), memory (b_1) and judgment (c_1) in PRJ model. There are 3 pathways, summarized as the fast processing pathway (f_1), the fine processing pathway $(d_1, d_2$ and $d_3)$, and the feedback processing pathway $(e_1$ and $e_2)$. The perception, memory and judgment of the cognitive process are respectively corresponding with time dependent mapping that the analysis of the computational process (A), modeling (B) and decisions (D) as follows Equation (7).

$$pmj: \quad <P_t,M_t,J_t> \rightarrow <A_t,B_t,D_t>$$
$$s.t. \begin{cases} p: <P_t,M_t,J_t,P_{t-1}> \rightarrow A_t \\ m: <P_t,M_t,J_t,M_{t-1}> \rightarrow B_t \\ j: <P_t,M_t,J_t,J_{t-1}> \rightarrow D_t \end{cases} \quad (7)$$

F. Cognitive Architecture for Media Computing

As Fig. 18 shows that the cognitive framework for brain-inspired processing of audio-visual can be divided into four steps [44]. That is, computation and simulation of cortical columns belief, computation and simulation of control information of thalamus for attention, computation and simulation of control information of limbic system for emotion, and computation and simulation of control information of spatio-temporal semantic caching of hippocampus for memory.

Fig. 18. Cognitive architecture of media computing.

The whole strategy of the media information processing process is training and reinforcement layer by layer. It includes 2 steps pre-learning algorithm in waking (PLAW) and precisely adjust algorithm in sleeping (PAAS) as follows:

1. PLAW mimics cognitive function is controlled by emotion and memory under the waking state. It is unsupervised training and using bottom-up and to pre-process input information of temporal media A and spatial media V step by step, and generate a set of MNCC initial parameters.

2. PAAS mimics cognitive function of sleeping state when thalamus closed the input information of temporal media A and spatial media V. It is supervised training, and top-down adjusts and optimizes internal parameters with hierarchical reinforcement learning strategies under the memory and emotional control.

The reward function of the limbic system is designed by the "principle of lowest energy" and "maximizing benefit" of the system. That is, rewarding successes and punishing failure.

G. Formal Semantics of CCNC Framework Based on Chemical Abstract Machine

The mind and brain is the physical and chemical reaction of biology. In order to analyze rationality of CCNC architecture, the CHemical Abstract Machine (CHAM) [59],[60] was employed. CHAM is a kind of description language architecture for parallel and dynamic software architecture analysis and testing. CHAM describes intelligent system architecture with molecules EH (e.g., hormones, neurotransmitters, and receptors), solution SS (e.g., state, semantic) and rules TS (e.g., knowledge, association, mapping). The CHAM molecular EH denoted factors of the chemical systems such as hormones, receptors, and transmitters, which affect the function of the physical system in the nervous system and cognitive architecture.

$$EH=EH_{SC}, EH_{DL}, EH_{RL}, EH_{IL}, EH_{CC}, EH_{EL}$$

The connecting elements C, processing elements TS (such as knowledge, rule, association, and mapping) and data elements D was defined as follows:

$$M::=TS|C \diamond EH|EH \diamond C|EH \diamond EH$$

$$C::=i(D)|o(D)|g(EH)|d(EH)$$

$$TS::=SC|IL|EL|RL|DL|CC$$

$$D::=Mi|Sa|Sv|Fa|Fv|Ma|Mv|Ms|Mt|Mp|Ei|Es|Cs|Ct|Cp|EH$$

where i(.) denoted the input, o(.) denoted the output, g(.) denoted the effects on the system input of the generation of hormones and transmitters, d(.) denoted the effects on the system output of the receptors receiving hormone and transmitter. The initial solution SS was defined as follows:

$$SS = SS_{SC}//SS_{DL}//SS_{CC}//SS_{EL}//SS_{RL}//SS_{IL}$$

where sub-solution is denoted as follows:

$$SS_{SC} = \{|i(Mi) \diamond i(Mn) \diamond i(Es) \diamond g(EH_{SC}) \diamond SC \diamond o(Sa) \diamond o(Sv) \diamond d(EH_{SC})|\}$$

$$SS_{DL} = \{|i(Sa) \diamond i(Ma) \diamond g(EH_{DL}) \diamond DL \diamond o(Fa) // i(Sv) \diamond i(Mv) \diamond DL \diamond o(Fv) \diamond d(EH_{DL})|\}$$

$$SS_{RL} = \{|i(Cp) \diamond g(EH_{RL}) \diamond RL \diamond o(Ei) \diamond o(Es) \diamond d(EH_{RL})|\}$$

$$SS_{IL} = \{|i(Ei) \diamond i(Cp) \diamond g(EH_{IL}) \diamond IL \diamond o(Mp) \diamond o(Ma) \diamond o(Mv) \diamond o(Mt) \diamond o(Ms) \diamond d(EH_{IL})|\}$$

$$SS_{CC} = \{|i(Fa) \diamond i(Mt) \diamond g(EH_{CC}) \diamond CC \diamond o(Ct) \diamond d(EH_{CC}) // i(Fv) \diamond i(Ms) \diamond g(EH_{CC}) \diamond CC \diamond o(Cs) \diamond d(EH_{CC})|\}$$

$$SS_{EL} = \{|i(Ct) \diamond i(Cs) \diamond i(Fa) \diamond i(Fv) \diamond g(EH_{EL}) \diamond EL \diamond o(Cp) \diamond d(EH_{EL})|\}$$

The intermediate solution SM after the reaction was defined as follows:

$$SM = SM_{SC} // SM_{DL} // SM_{CC} // SM_{EL} // SM_{RL} // SM_{IL}$$

where the sub-solution is denoted as follows:

$$SM_{SC} = \{|SC \diamond i(Mi) \diamond i(Mn) \diamond i(Es) \diamond g(EH_{SC}) \diamond o(Sa) \diamond o(Sv) \diamond d(EH_{SC})|\}$$

$$SM_{DL} = \{|DL \diamond i(Sa) \diamond i(Ma) \diamond g(EH_{DL}) \diamond o(Fa) // DL \diamond i(Sv) \diamond i(Mv) \diamond o(Fv) \diamond d(EH_{DL})|\}$$

$$SM_{RL} = \{|RL \diamond i(Cp) \diamond g(EH_{RL}) \diamond o(Ei) \diamond o(Es) \diamond d(EH_{RL})|\}$$

$$SM_{IL} = \{|IL \diamond i(Ei) \diamond i(Cp) \diamond g(EH_{IL}) \diamond o(Mp) \diamond o(Ma) \diamond o(Mv) \diamond o(Mt) \diamond o(Ms) \diamond d(EH_{IL})|\}$$

$$SM_{CC} = \{|CC \diamond i(Fa) \diamond i(Mt) \diamond g(EH_{CC}) \diamond o(Ct) \diamond d(EH_{CC}) // CC \diamond i(Fv) \diamond i(Ms) \diamond g(EH_{CC}) \diamond o(Cs) \diamond d(EH_{CC})|\}$$

$$SM_{EL} = \{EL \diamond | i(Ct) \diamond i(Cs) \diamond i(Fa) \diamond i(Fv) \diamond g(EH_{EL}) \diamond o(Cp) \diamond d(EH_{EL})|\}$$

The 6 important basic rules for the solution reaction (state transition) were defined as follows:

$$TS_{SC} \equiv i(Mi) \diamond i(Mn) \diamond i(Es) \diamond g(EH_{SC}) \diamond SC, o(Sa) \diamond o(Sv) \diamond d(EH_{SC}) \diamond SC \rightarrow SC \diamond i(Mi) \diamond i(Mn) \diamond i(Es) \diamond g(EH_{SC}), SC \diamond o(Sa) \diamond o(Sv) \diamond d(EH_{SC})$$

$$TS_{DL} \equiv i(Sa) \diamond i(Ma) \diamond g(EH_{DL}) \diamond DL, o(Fa) \diamond d(EH_{DL}) \diamond DL, i(Sv) \diamond i(Mv) \diamond g(EH_{DL}) \diamond DL, o(Fv) \diamond d(EH_{DL}) \diamond DL \rightarrow DL \diamond i(Sa) \diamond i(Ma) \diamond g(EH_{DL}), DL \diamond o(Fa) \diamond d(EH_{DL}), DL \diamond i(Sv) \diamond i(Mv) \diamond g(EH_{DL}), DL \diamond o(Fv) \diamond d(EH_{DL})$$

$$TS_{RL} \equiv i(Cp) \diamond g(EH_{RL}) \diamond RL, o(Ei) \diamond o(Es) \diamond d(EH_{RL}) \diamond RL \rightarrow RL \diamond i(Cp) \diamond g(EH_{RL}), RL \diamond o(Ei) \diamond o(Es) \diamond d(EH_{RL})$$

$TS_{IL} \equiv i(Ei) \diamond i(Cp) \diamond g(EH_{IL}) \diamond IL, o(Mp) \diamond o(Ma) \diamond o(Mv) \diamond o(Mt) \diamond o(Ms) \diamond d(EH_{IL}) \diamond IL \rightarrow IL \diamond i(Ei) \diamond i(Cp) \diamond g(EH_{IL}), IL \diamond o(Mp) \diamond o(Ma) \diamond o(Mv) \diamond o(Mt) \diamond o(Ms) \diamond d(EH_{IL})$

$TS_{CC} \equiv i(Fa) \diamond i(Mt) \diamond g(EH_{CC}) \diamond CC, o(Ct) \diamond d(EH_{CC}) \diamond CC, i(Fv) \diamond i(Ms) \diamond g(EH_{CC}) \diamond CC, o(Cs) \diamond d(EH_{CC}) \diamond CC \rightarrow CC \diamond i(Fa) \diamond i(Mt) \diamond g(EH_{CC}), CC \diamond o(Ct) \diamond d(EH_{CC}), CC \diamond i(Fv) \diamond i(Ms) \diamond g(EH_{CC}), CC \diamond o(Cs) \diamond d(EH_{CC})$

$TS_{EL} \equiv i(Ct) \diamond i(Cs) \diamond i(Fa) \diamond i(Fv) \diamond g(EH_{EL}) \diamond EL, o(Cp) \diamond d(EH_{EL}) \diamond EL \rightarrow EL \diamond i(Ct) \diamond i(Cs) \diamond i(Fa) \diamond i(Fv) \diamond g(EH_{EL}), EL \diamond o(Cp) \diamond d(EH_{EL})$

The rules TS_{SC} denoted the saliency computation of the attention mechanism in thalamic-cortical circuits. Thalamic-cortical projection is an important infrastructure of brain function, and the thalamus plays an important role in the attention mechanism. Selective attention can reduce the influence of curse of dimensionality by saliency mechanism. In order to realize the saliency computation, this process focuses on the attention mechanism of the thalamic-cortical circuit and establishes the scheme of the saliency feature extraction. This rule mapping between the media *MM* and the spatial-temporal saliency features *<Sa, Sv>* was indicated as follows Equation (8).

$$SC: MM \rightarrow \langle Sa, Sv \rangle$$
$$s.t. \quad \langle Sa, Sv \rangle = \prod_{\langle Mn, Es \rangle} \sigma_{Mn}(MM) \tag{8}$$

The rules TS_{DL} denotes the senses feature learning based on the hierarchical structure of the cortex. A cortical column is the basic unit of cognitive function. The cortex cognitive function is deep learning algorithm research basis and inspires how to realize the target classification and recognition. We can emulate the processing mechanism of the multi-layers architecture of the cortical column, and design the hierarchical semantic classifier. The probability distribution of the spatial-temporal senses features *<Fa,Fv>* was computed with media objects saliency features as follows Equation (9).

$$DL: \{\langle Sa, Ma \rangle \langle Sv, Mv \rangle\} \rightarrow \langle Fa; Fv \rangle$$
$$s.t. \quad DL = F_n\left(F_{n-1}\left(F_{n-2}\left(\cdots, F_2(F_1(x)), \cdots, \right)\right)\right) \tag{9}$$

The rules TS_{CC} denoted perceptual features computation based on probabilistic cognition. The computation process of the perceptual feature is building the mapping between Bayesian probability distribution of spatial-temporal senses features *<Fa,Fv>* and spatial-temporal perceptual features *<Ct, Cs>* as follows Equation (10).

$$CC: \{\langle Fa, Mt \rangle; \langle Fv, Ms \rangle\} \rightarrow \{Ct; Cs\}$$
$$s.t. \quad \underset{\{Ct;Cs\}}{argmax} P(\{Ct;Cs\} | \{\langle Fa, Mt \rangle; \langle Fv, Ms \rangle\})$$
$$= \frac{P(\{\langle Fa, Mt \rangle; \langle Fv, Ms \rangle\} | \{Ct;Cs\}) P(\{Ct;Cs\})}{P(\{\langle Fa, Mt \rangle; \langle Fv, Ms \rangle\})} \tag{10}$$

The rules TS_{EL} denoted target recognition based on multi-modal perception integration. It realizes the Ensemble Learning (EL) of multi-modal perception information and the final decision making of target semantic recognition. The core mission of target recognition is to establish the mapping between spatial-temporal senses-perceptual features *<Ct, Cs, Fa, Cp, Fv>* and target semantic labels as follows Equation (11)..

$$EL: \langle Cs, Ct, Fv, Fa | DL, CC \rangle \rightarrow Cp$$
$$s.t. \quad Cp = sign(\sum_m w_m f_m(\langle Cs, Ct, Fv, Fa | DL, CC \rangle)) \tag{11}$$

The rules TS_{RL} denoted the reward and punishment of emotion in the limbic system. It is the Reinforcement Learning (RL) basis that the emotions control of reward and punishment in the limbic system. The aim of simulating emotion control of rewards and punishment is to establish a stable and optimal target semantic. This rule solves errors minimization paradigm between the target semantic expectation *Cp* and the saliency feedback (*Ei* and *Es*) was defined as as follows Equation (12).

$$\underset{\|RL\|}{\overset{\|RL\|}{argMin}}(\|Cp_L - \overline{Cp}\|) \qquad s.t. \quad RL: \langle Cp | CC \rangle \rightarrow \langle Ei, Es \rangle \tag{12}$$

The rules TS_{IL} denoted the control of the memory system. The essence of semantic mapping is the memory and prediction for the spatial-temporal pattern. The material base for intelligent prediction includes the memory processing architecture of cortex-hippocampus circuits and its spatial-temporal pattern. This rule imitated mechanism of memory control, and storage and prediction of the historical information. The rules employed Incremental Learning (IL) method to control incremental knowledge. It includes the incremental of DNN's spatial-temporal features *<Mt,Ms>*, the incremental of cognitive topic spatial-temporal features *<Mt,Ms>*, and memory feedback *Mp* of incremental learning as follows Equation (13).

$$IL: \langle Ei, Cp | DL, CC \rangle \rightarrow \langle Mp, Ma, Mv, Mt, Ms, Mn \rangle$$
$$s.t. \quad M_t = \frac{\alpha M_{t-1} Ei}{1 + sgn(\Delta t) exp(\gamma \Delta t sgn(\Delta t))} + \beta Cp,$$
$$M_t = Mp_t, Ma_t, Mv_t, Mt_t, Ms_t, Mn_t \tag{13}$$

H. Algorithms Description for Semantic Learning and Recognition of Hierarchical CCNC Framework

The hierarchical CCNC framework semantic learning algorithm is dynamic process. It includes the following 8 steps as follows:

1:	It achieves spatial-temporal saliency features computation based on SNN according to the rules of TS_{SC}.
	$SS_{SC} // SS_{DL} // SS_{CC} // SS_{EL} // SS_{RL} // SS_{IL} \rightarrow SM_{SC} // SS_{DL} // SS_{CC} // SS_{EL} // SS_{RL} // SS_{IL}$
2:	It achieves target semantic learning of hierarchically integrated cognition based on deep learning and cognitive computing, including 3 dynamic processes as follows:
3:	It realizes spatial-temporal senses features computation of DNN according to the rules of TS_{DL}.
	$SM_{SC} // SS_{DL} // SS_{CC} // SS_{EL} // SS_{RL} // SS_{IL} \rightarrow SM_{SC} // SM_{DL} // SS_{CC} // SS_{EL} // SS_{RL} // SS_{IL}$
4:	It realizes spatial-temporal perception features computation of hierarchical topic model according to the rules of TS_{CC}.
	$SM_{SC} // SM_{DL} // SS_{CC} // SS_{EL} // SS_{RL} // SS_{IL} \rightarrow SM_{SC} // SM_{DL} // SM_{CC} // SS_{EL} // SS_{RL} // SS_{IL}$
5:	It realizes ensemble learning of objects semantic labels based on ensemble learning (such as AdaBoost et.al.) according to the rules of TS_{EL}.
	$SM_{SC} // SM_{DL} // SM_{CC} // SS_{EL} // SS_{RL} // SS_{IL} \rightarrow SM_{SC} // SM_{DL} // SM_{CC} // SM_{EL} // SS_{RL} // SS_{IL}$
6:	It achieves incremental computation and feedback of reinforcement learning based on object-oriented and multi-scale, including 2 dynamic processes as follows:
7:	It realizes multi-scale feedback computation of hierarchy reinforcement learning according to the rules of TS_{RL}.
	$SM_{SC} // SM_{DL} // SM_{CC} // SM_{EL} // SS_{RL} // SS_{IL} \rightarrow SM_{SC} // SM_{DL} // SM_{CC} // SM_{EL} // SM_{RL} // SS_{IL}$
8:	It realizes the temporal-spatial computation of object-oriented target based on online incremental learning according to the rules of TS_{IL}.
	$SM_{SC} // SM_{DL} // SM_{CC} // SM_{EL} // SM_{RL} // SS_{IL} \rightarrow SM_{SC} // SM_{DL} // SM_{CC} // SM_{EL} // SM_{RL} // SM_{IL}$

The hierarchical CCNC framework semantic recognition algorithm is also dynamic process. It includes the following 5 steps as follows:

1:	It achieves the saliency feature computation of sparse representation of SNN.
	$SS_{SC} // SS_{DL} // SS_{CC} // SS_{EL} // SM_{RL} // SM_{IL} \rightarrow SM_{SC} // SS_{DL} // SS_{CC} // SS_{EL} // SM_{RL} // SM_{IL}$
2:	It achieves target recognition of hierarchically integrated cognition based on deep learning and cognitive computing, including 3 processes as follows:
3:	It realizes spatial-temporal senses feature computation of DNN according to the rules of TS_{DL}.
	$SM_{SC} // SS_{DL} // SS_{CC} // SS_{EL} // SM_{RL} // SM_{IL} \rightarrow SM_{SC} // SM_{DL} // SS_{CC} // SS_{EL} // SM_{RL} // SM_{IL}$
4:	It realizes spatial-temporal perception features computation of hierarchical topic model according to the rules of TS_{CC}.
	$SM_{SC} // SM_{DL} // SS_{CC} // SS_{EL} // SM_{RL} // SM_{IL} \rightarrow SM_{SC} // SM_{DL} // SM_{CC} // SS_{EL} // SM_{RL} // SM_{IL}$
5:	It realizes ensemble computation of objects semantic labels based on ensemble learning (such as AdaBoost et.al.) according to the rules of TS_{EL}.
	$SM_{SC} // SM_{DL} // SM_{CC} // SS_{EL} // SM_{RL} // SM_{IL} \rightarrow SM_{SC} // SM_{D}L // SM_{CC} // SM_{EL} // SM_{RL} // SM_{IL}$

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