

## **A Doctrine of Cognitive Informatics (CI)**

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**Streszczenie.** Cognitive informatics (CI) is the transdisciplinary enquiry of cognitive and information sciences that investigates into the internal information processing mechanisms and processes of the brain and natural intelligence, and their engineering applications via an interdisciplinary approach. CI develops a coherent set of fundamental theories and denotational mathematics, which form the foundation for most information and knowledge based science and engineering disciplines such as computer science, cognitive science, neuropsychology, systems science, cybernetics, software engineering, knowledge engineering, and computational intelligence. This paper reviews the central doctrine of CI and its applications. The theoretical framework of CI is described on the architecture of CI and its denotational mathematic means. A set of theories and formal models of CI is presented in order to explore the natural and computational intelligence. A wide range of applications of CI are described in the areas of cognitive computers, cognitive properties of knowledge, simulations of human cognitive behaviors, cognitive complexity of software, autonomous agent systems, and computational intelligence.

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## 1. Introduction

The history of human quest to understand the brain and natural intelligence is certainly as long as human history itself [19]. The development of classical and contemporary informatics, the cross fertilization between computer science, systems science, software science, cybernetics, cognitive science, neuropsychology, knowledge engineering, computational intelligence, and life science, has led to an entire range of the extremely interesting new research field known as *Cognitive Informatics* (CI) [8, 16, 22, 32, 34, 35, 36, 39, 57, 59, 63, 66, 73]. CI is a cutting-edge and profound interdisciplinary research area that tackles the fundamental problems shared among aforementioned disciplines. Almost all of the hard problems yet to be solved in these areas can be deduced onto the common root for understanding the mechanisms of natural intelligence and cognitive processes of the brain.

It is recognized that information is any property or attribute of the natural world that can be distinctly elicited, generally abstracted, quantitatively represented, and mentally processed. Information is the third essence of the natural world supplementing matter and energy. Informatics is the science of information that studies the nature of information, its processing, and ways of transformation between information, matter and energy. CI is a new discipline that studies the natural intelligence and internal information processing mechanisms of the brain, as well as processes involved in perception and cognition. CI forges links between a number of natural science and life science disciplines with informatics and computing science.

A number of fundamental human wonders from the context of CI, such as: How consciousness is generated as a highly complex cognitive state in human mind on the basis of physiological metabolism? How natural intelligence is generated on the basis of basic biological and physiological structures? How intelligence functions logically and physiologically? And how natural and machine intelligence are converged on the basis of CI and computational intelligence?

This paper surveys the doctrine of CI and its applications. The theoretical framework of CI is described in Section 2 on the architecture of CI, denotational mathematics for CI, and highlights of some CI events. A set of basic theories and formal models of CI is elaborated in Section 3, which form a foundation for exploring the natural intelligence and their applications in brain science, neural informatics, computing, knowledge engineering, and software engineering. Applications of CI are described in Section 4, which cover cognitive computing, estimation of the capacity of human memory, cognitive properties of knowledge, simulations of human cognitive behaviors based on denotational mathematics, cognitive complexity of software, autonomous agent systems, inferential modeling techniques, and cognitive networks with machine learning.

## 2. The Theoretical Framework of Cognitive Informatics

The theories of informatics and their perceptions on the object of information have evolved from the classic information theory, modern informatics, to cognitive informatics in the last six decades. *Conven-*

tional information theories [2, 26], particularly Shannon's information theory [26] known as the first-generation informatics, study signals and channel behaviors based on statistics and probability theory. *Modern informatics* studies information as properties or attributes of the natural world that can be generally abstracted, quantitatively represented, and mentally processed. The first- and second-generation informatics put emphases on external information processing, which overlook the fundamental fact that human brains are the original sources and final destinations of information, and any information must be cognized by human beings before it is understood. This observation leads to the establishment of the third-generation informatics, a term coined by Wang in 2002 as CI in [32].

**Definition 1.** *CI* is the transdisciplinary enquiry of cognitive and information sciences that investigates into the internal information processing mechanisms and processes of the brain and natural intelligence, and their engineering applications via an interdisciplinary approach.

## 2.1. Highlights on Events of Cognitive Informatics

A series of IEEE International Conferences on Cognitive Informatics (ICCI) have been annually organized. The inaugural ICCI event in 2002 was held at Calgary, Canada (ICCI'02) [57], followed by the events in London, UK (ICCI'03) [22]; Victoria, Canada (ICCI'04) [8]; Irvine, USA (ICCI'05) [16]; Beijing, China (ICCI'06) [66]; Lake Tahoe, USA (ICCI'07) [73]; and Stanford University, USA (ICCI'08) [63].

A number of keynotes have been presented in the IEEE Series of International Conferences on Cognitive Informatics (ICCI'02 - ICCI'08) as highlighted as follows.

Lotfi A. Zadeh presents the latest keynote in ICCI'08 on "*Toward Human Level Machine Intelligence - Is It Achievable?* [72]" He pointed out that achievement of human level machine intelligence has long been one of the basic objectives of AI. Since its born in 1956, very impressive progress has been made except in the realm of human level machine intelligence. This indicates that to achieve human level machine intelligence is a challenge that is hard to meet, because humans have many remarkable capabilities; there are two that stand out in importance. First, the capability to reason, converse, and make rational decisions in an environment of imprecision, uncertainty, incompleteness of information, and partiality of truth and possibility. And second, the capability to perform a wide variety of physical and mental tasks without any measurements and any computations. A prerequisite to achievement of human level machine intelligence is mechanization of these capabilities and, in particular, mechanization of natural language understanding, which may be beyond the reach of the armamentarium of AI that, in large measure, employs classical, Aristotelian, bivalent logic, and bivalent-logic-based probability theory. To make progress toward achievement of human level machine intelligence, AI must add to its armamentarium concepts and techniques drawn from other methodologies, especially evolutionary computing, neurocomputing and fuzzy logic. Addition of this machinery to the armamentarium of AI would be an important step toward the achievement of human level machine intelligence and its applications in decision-making, pattern recognition, analysis of evidence, diagnosis, and assessment of causality.

James Anderson presented a keynote in ICCI'05 entitled "*Cognitive Computation: The Ersatz Brain Project* [1]", which offered some exciting glimpses on an ambitious project to build a brain-like computing system. The talk focused on the progress made in three areas: preliminary hardware design, programming techniques, and software applications. The proposed hardware architecture, based on ideas from mammalian neo-cortex, is a massively parallel and two-dimensional locally connected array of CPUs

and their associated memory. What makes this design feasible is an approximation to cortical function called the *Network of Networks* which indicates that the basic computing unit in the cortex is not a single neuron but small groups of neurons working together to form attractor networks. Thus, each network of networks module corresponds to a single CPU in the hardware design. A system with approximately the power of a human cerebral cortex would require about a million CPUs and a terabyte of data specifying the connection strengths using the network of networks approach. To develop “cognitive” software for such a brain-like computing system, there needs to be some new programming techniques such as topographic data representation, lateral data movement, and use of interconnected modules for computation. The software applications involve language, cognitive data analysis, visual information processing, decision making, and knowledge management.

Jean-Claude Latombe presented a keynote in ICCI'06 entitled “*Probabilistic Roadmaps: A Motion Planning Approach Based on Active Learning* [18].” This talk focused on motion planning of autonomous robots. A new motion-planning approach - Probabilistic RoadMap (PRM) planning - was presented. PRM planning trades the prohibitive cost of computing the exact shape of a feasible space against the cost of learning its connectivity from dynamically chosen examples (the sampled configurations). PRM planning, a widely popular approach in robotics, is extremely successful in solving apparently very complex motion planning problems with various feasibility constraints. The talk touched the foundations of PRM planning and explained why it is so successful. The PRM success reveals key properties satisfied by feasible spaces encountered in practice. Furthermore, a better understanding of these properties is already making it possible to design faster PRM planners capable of solving increasingly more complex problems.

Yingxu Wang presented a keynote in ICCI'06 on “*Cognitive Informatics: Toward Future Generation Computers that Think and Feel* [36].” He reviewed a set of the latest advances in CI that may lead to the design and implementation of cognitive computers capable of thinking and perceiving. He pointed out that CI provides the theory and philosophy for the next generation computers and computing paradigms. Recent advances in CI were discussed in two groups, namely, an entire set of cognitive functions and processes of the brain and an enriched set of denotational mathematics. He described the approach to cognitive computing for cognitive and perceptible concept/knowledge processing, based on denotational mathematics such as concept algebra, system algebra, and RTPA. Cognitive computers implement the fundamental cognitive processes of the natural intelligence such as the learning, thinking, formal inferences, and perception processes. They are novel information and knowledge processing systems that think and feel. In contrary to the von Neumann architecture for traditional stored-program controlled imperative computer, the speaker elaborated on a computational intelligent architecture of next generation computing, which is an applause step toward the development of cognitive computers.

Witold Kinsner's keynote in ICCI'06 presented “*Some Advances in Cognitive Informatics* [17].” He took a closer look at the recent advances in signal processing for autonomic computing and its metrics. Autonomic computing is geared toward mitigating the escalating complexity of a software system in both its features and interfaces by making the system self-configuring, self-optimizing, self-organizing, self-healing, self-protecting and self-communicating. Because signal processing is used in nearly all fields of human endeavor ranging from signal detection, fault diagnosis, advanced control, audio and image processing, communications engineering, intelligent sensor systems, and business, it will play a pivotal role in developing autonomic computing systems. The classical statistical signal processing nowadays is augmented by intelligent signal processing which utilizes supervised and unsupervised learning through adaptive neural networks, wavelets, fuzzy rule-based computation and rough sets, genetic algorithms,

and blind signal estimation. Quality metrics are needed to measure the quality of various multimedia materials in perception, cognition and evolutionary learning processes, to gauge the self-awareness in autonomic systems, and to assess symbiotic cooperation in evolutionary systems. Instead of energy-based metrics, the multi-scale metrics based on fractal dimensions are found to be most suited for perception.

Since its inception in 2002, ICCI has been growing steadily in both its size and scope. It attracts both researchers from academia, government agencies, and industry practitioners from many countries. The conferences provide a main forum for the exchange and cross-fertilization of ideas in the new research areas of CI. The research interest in this niche area from all over the world is growing and the body of work produced thus far has been taking shape in both quality and quantity.

## 2.2. The Architecture of Cognitive Informatics

Information is recognized as the third essence of the natural world supplementing to matter and energy [35], because the primary function of the human brain is information processing.

**Definition 2.** A generic world view, the *Information-Matter-Energy (IME) model*, states that the natural world ( $NW$ ), which forms the context of human beings is a dual world: one aspect of it is the physical or the concrete world ( $PW$ ), and the other is the abstract or the perceptive world ( $AW$ ), where *matter* ( $M$ ) and *energy* ( $E$ ) are used to model the former, and *information* ( $I$ ) to the latter, i.e.:

$$\begin{aligned} NW &\triangleq PW \parallel AW \\ &= \mathcal{P}(M, E) \parallel \mathcal{A}(I) \\ &= \mathcal{N}(I, M, E) \end{aligned} \quad (1)$$

where  $\parallel$  denotes a parallel relation, and  $\mathcal{P}$ ,  $\mathcal{A}$ , and  $\mathcal{N}$  are functions that determine a certain  $PW$ ,  $AW$ , or  $NW$ , respectively, as illustrated in Fig. 1.

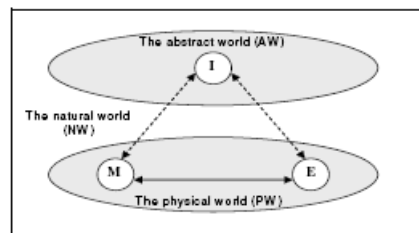


Figure 1. The IME model of the worldview of CI

According to the IME model, information plays a vital role in connecting the physical world with the abstract world. It is recognized that the basic evolutionary need of mankind is to preserve both the species' biological traits and the cumulated information/knowledge bases. For the former, the gene pools are formed to pass human trait information via DNA from generation to generation. However, for the latter, because acquired knowledge cannot be inherited between generations and individuals, various information means and systems are adopted to pass cumulated human information and knowledge.

Models of the natural world have been well studied in physics and other natural sciences. However, the modeling of the abstract world is still a fundamental issue yet to be explored in cognitive informatics. Especially the relationships between I-M-E and their transformations are deemed as one of the fundamental questions.

An intensive review on *The Theoretical Framework of Cognitive Informatics* was presented in [39], which provides a coherent summary of the latest advances in the transdisciplinary field of CI and an insightful perspective on its future development. The architecture of the theoretical framework of CI covers the Layered Reference Model of the Brain (LRMB) [60], the Object-Attribute-Relation (OAR) model of information representation in the brain [40], the cognitive informatics model of the brain [61], Natural Intelligence (NI) [35, 55], Neural Informatics (NeI) [39], the mechanisms of human perception processes [44], cognitive computing [36], and cognitive machines [17].

The key application areas of CI can be divided into two categories. The first category of applications uses informatics and computing techniques to investigate cognitive science problems, such as memory, learning, and reasoning. The second category including the areas that use cognitive theories to investigate problems in informatics, computing, software engineering, knowledge engineering, and computational intelligence. CI focuses on the nature of information processing in the brain, such as information acquisition, representation, memory, retrieve, generation, and communication. Through the interdisciplinary approach and with the support of modern information and neuroscience technologies, mechanisms of the brain and the mind may be systematically explored within the framework of CI.

### 2.3. Denotational Mathematics for Cognitive Informatics

The history of sciences and engineering shows that many branches of mathematics have been created in order to meet their abstract, rigorous, and expressive needs. These phenomena may be conceived as that new problems require new forms of mathematics [3, 23, 70, 71] and the maturity of a scientific discipline is characterized by the maturity of its mathematical means [38]. Applied mathematics can be classified into two categories known as *analytic* and *denotational* mathematics [33, 38, 41, 46, 54]. The former are mathematical structures that deal with functions of variables and their operations and behaviors; while the latter are mathematical structures that formalize rigorous expressions and inferences of system architectures and behaviors with data, concepts, and dynamic processes.

**Definition 3.** *Denotational mathematics* is a category of expressive mathematical structures that deals with high level mathematical entities beyond numbers and sets, such as abstract objects, complex relations, behavioral information, concepts, knowledge, processes, and systems.

The denotational and expressive needs in cognitive informatics, computational intelligence, software engineering, and knowledge engineering lead to new forms of mathematics collectively known as denotational mathematics. Typical forms of denotational mathematics [38, 46, 54] are comparatively presented in Table 1, where their structures, mathematical entities, algebraic operations, and usages are contrasted. The paradigms of denotational mathematics as shown in Table 1 are *concept algebra* [47], *system algebra* [48, 64], *Real-Time Process Algebra (RTPA)* [33, 49, 50, 51, 54], and *Visual Semantic Algebra (VSA)* [52].

The emergence of denotational mathematics is driven by the practical needs in cognitive informatics, computational intelligence, cognitive computing, software science, and knowledge engineering, because all these modern disciplines study complex human and machine behaviors and their rigorous treatments.

Table 1. Paradigms of Denotational Mathematics

Paradigm	Structure	Mathematical entities	Algebraic operations	Usage
Concept algebra	$CA \hat{=} (C, OP, \Theta) =$ $= (\{O, A, R^c, R^i, R^0\},$ $\{\bullet_r, \bullet_c\}, \Theta_c)$	$c \hat{=} (O, A, R^c, R^i, R^0)$	$\bullet_r \hat{=} \{\leftrightarrow, \nleftrightarrow, \prec, \succ, =, \cong, \sim, \hat{=}\}$ $\bullet_c \hat{=} \{\Rightarrow, \bar{\Rightarrow}, \overset{+}{\Rightarrow}, \tilde{\Rightarrow}, \Updownarrow, \Downarrow, \Leftarrow, \vdash, \mapsto\}$	Algebraic manipulations on abstract concepts
System algebra	$SA \hat{=} (S, OP, \Theta) =$ $= (\{C, R^c, R^i, R^0, B, \Omega\},$ $\{\bullet_r, \bullet_c\}, \Theta)$	$S \hat{=} (C, R^c, R^i, R^0, B, \Omega, \Theta)$	$\bullet_r \hat{=} \{\nleftrightarrow, \leftrightarrow, \perp, \sqcup, =, \sqsubseteq, \sqsupseteq\}$ $\bullet_c \hat{=} \{\Rightarrow, \bar{\Rightarrow}, \overset{+}{\Rightarrow}, \tilde{\Rightarrow}, \boxplus, \boxminus, \boxtimes, \boxdiv, \Leftarrow, \vdash\}$	Algebraic manipulations on abstract systems
Real-time process algebra (RTPA)	$RTPA \hat{=} (\mathfrak{A}, \mathfrak{P}, \mathfrak{R})$	$\mathfrak{A} \hat{=} \{ := \blacklozenge, \Rightarrow, \Leftarrow, \nrightarrow, \succ, \prec,  \succ,   \prec, @, \hat{=}, \uparrow, \downarrow, !, \otimes, \boxtimes, \S \}$  $\mathfrak{P} \hat{=} \{ \mathbf{N, Z, R, S, BL, BH, P, TI, D, DT, RT, ST, @eS, @t, TM, @int\odot, @sBL} \}$	$\mathfrak{R} \hat{=} \{ \rightarrow, \curvearrowright,  ,   \dots  , \dots R^*, R^+, R^i, \odot, \succ, \parallel, \boxplus, \boxtimes, \boxminus, \boxdiv, \gg, \zeta, \hookrightarrow_t, \hookrightarrow_e, \hookrightarrow_i \}$	Algebraic manipulations on abstract processes
Visual semantic algebra (VSA)	$VSA \hat{=} (O, \bullet_{VSA} = (\{H \cup S \cup F \cup L\}, \bullet_{VSA}))$	$H \hat{=} \{ \bullet, -, \angle, \frown, \Delta, \square, \square, \square, \diamond, \circ, \circ \}$ $S \hat{=} \{ C?, R?, C?, S?, C?, P? \}$ $F \hat{=} \{ \uparrow, \S, \oplus \}$ $L \hat{=} \{ \top, \perp, \vdash, \dashv, [ , ] \}$	$\bullet_{VSA} \hat{=} \{ \uparrow, \downarrow, \leftarrow, \rightarrow, \odot, \otimes, \boxplus, \angle, @, .(p), @(x,y,x), \curvearrowright \}$	Algebraic manipulations on abstract visual semantics

Among the four forms of denotational mathematics, *concept algebra* is designed to deal with the new abstract mathematical structure of concepts and their representation and manipulation in knowledge engineering. *System algebra* is created to the rigorous treatment of abstract systems and their algebraic relations and operations. RTPA is developed for algebraically denoting and manipulating system behavioural processes and their attributes. VSA is developed for the formal modeling and manipulation of abstract visual objects and patterns. Applications of denotational mathematics in cognitive informatics and computational intelligence have been applied to a wide range of real-world case studies, which demonstrate that denotational mathematics is an ideal mathematical means for dealing with concepts, knowledge, behavioral processes, and human/machine intelligence across the disciplines of cognitive, software, and intelligence sciences.

### 3. Fundamental Theories and Models of Cognitive Informatics

The latest advances in CI have developed a coherent set of fundamental theories and formal models toward the understanding of the brain and natural intelligence. The key theories of CI are known as abstract intelligence and denotational mathematics. The latter has been introduced in Section 2.3, and the former will be reviewed in the following subsections.

#### 3.1. Abstract Intelligence: A Unified Theory of Natural, Artificial, Machinable, and Computational Intelligence

**Definition 4.** *Intelligence*, in the narrow sense, is a human or a system ability that transforms information into behaviors or actions; and in the broad sense, is any human or system ability that autonomously transfers the forms of abstract information among *data*, *information*, *knowledge*, and *behaviors* in the brain.

**Theorem 1.** The *Information-Matter-Energy-Intelligence* (IME-I) model states that the natural world (NW) which forms the context of human and machine intelligence is a dual: one aspect of it is the *physical world* (PW), and the other is the *abstract world* (AW), where *intelligence* ( $\Im$ ) plays a central role in the transformation between information (*I*), *matter* (*M*), and *energy* (*E*).

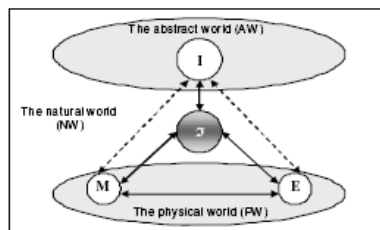


Figure 2. The IME-I model and roles of intelligence in CI

In the IME-I model as shown in Fig. 2, intelligence  $\Im$  plays an irreplaceable role in the transformation between information, matter, and energy, as well as different forms of internal information and knowledge.

**Theorem 2.** The principle of *compatible intelligent capability* states that, among various forms of intelligence such as those of *natural* (NI), *artificial* (AI), *machinable* (MI), and *computational* (CoI), the following relationships hold:

$$CoI \subseteq MI \subseteq AI \subseteq NI \quad (2)$$

The proof and elaboration of Theorem 2 has been provided in [55], where the behavioral domains of each form of intelligence have been formally modeled. Theorem 2 indicates that *AI* and its subsets of *CoI* and *MI* are dominated by NI. Therefore, one should not expect a computer or a machine to solve a problem where humans cannot. In other words, no AI or computing system may be designed and/or implemented for a given problem where there is no solution being known by human beings as a whole [45].

### 3.2. The Layered Reference Model of the Brain

The *Layered Reference Model of the Brain* (LRMB) [60] is developed to explain the fundamental cognitive mechanisms and processes of natural intelligence. Because a variety of life functions and cognitive processes have been identified in CI, psychology, cognitive science, brain science, and neurophilosophy, there is a need to organize all the recurrent cognitive processes in an integrated and coherent framework. The LRMB model explains the functional mechanisms and cognitive processes of natural intelligence that encompasses 39 cognitive processes at seven layers known as the *sensation*, *memory*, *perception*, *action*, *meta-cognitive*, *meta-inference*, and *higher cognitive layers* from the bottom-up as shown in Fig. 3. LRMB elicits the core and repetitively recurrent cognitive processes from a huge variety of life functions, which may shed light on the study of the fundamental mechanisms and interactions of complicated mental processes, particularly the relationships and interactions between the inherited and the acquired life functions as well as those of the subconscious and conscious cognitive processes.

It is noteworthy in LRMB that most inherited life functions are subconscious and unconscious. However, most of the acquired life functions are conscious. Although one cannot intentionally control the subconscious and unconscious processes in the brain, one may autonomously apply them repetitively every second with all conscious processes. The LRMB model [60] and the formal models of its 39 cognitive processes enable the simulation of human brain, the highest level of intelligence, in computational intelligence.

### 3.3. Neural Informatics (NeI)

**Definition 5.** *Neural Informatics* (NeI) is an emerging interdisciplinary enquiry of the biological and physiological representation of information and knowledge in the brain at the neuron level and their abstract mathematical models.

NeI is a branch of CI where memory is recognized as the foundation and platform of any natural or artificial intelligence [39].

**Theorem 3.** The *Cognitive Model of Memory* (CMM) states that the logical architecture of human memory is parallel configured by the Sensory Buffer Memory (SBM), Short-Term Memory (STM),

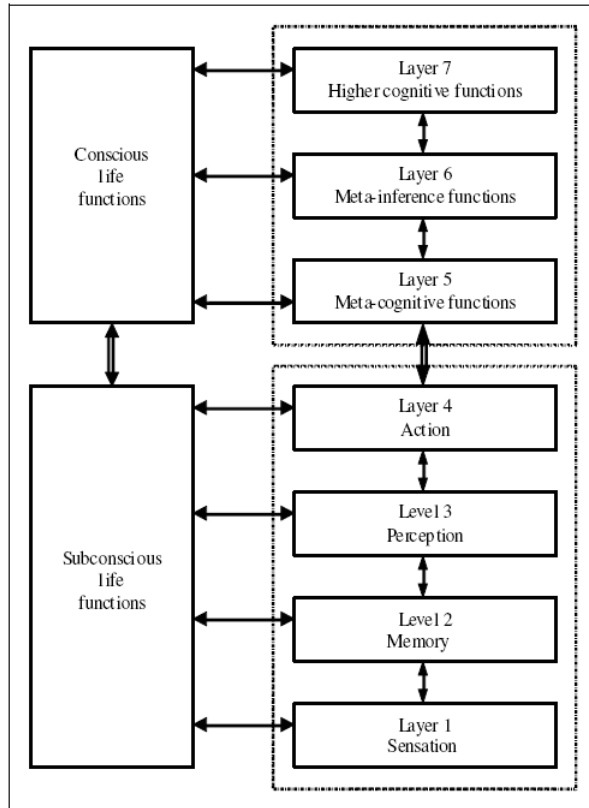


Figure 3. The Layered Reference Model of the Brain (LRMB)

Conscious-Status Memory (CSM), Long-Term Memory (LTM), and Action-Buffer Memory (ABM), i.e.:

$$\begin{aligned}
 \text{CMMST} &\hat{=} \text{SBM} \\
 &\parallel \text{STM} \\
 &\parallel \text{CSM} \\
 &\parallel \text{LTM} \\
 &\parallel \text{ABM}
 \end{aligned} \tag{3}$$

CMM provides a logical model for explaining the abstract functional partitions of memories and their roles. In theorem 3, ABM and CSM are newly identified in [61, 62].

The major organ that accommodates memories in the brain is the cerebrum or the cerebral cortex. In particular, the association and premotor cortex in the frontal lobe, the temporal lobe, sensory cortex in the frontal lobe, visual cortex in the occipital lobe, primary motor cortex in the frontal lobe, supplementary motor area in the frontal lobe, and procedural memory in cerebellum. The CMM model and the mapping of the five types of human memory onto the physiological organs in the brain reveal a set of fundamental mechanisms of NeI.

The theories of CI and NeI explain a number of fundamental questions in the study of natural intelligence. Enlightening results derived in CI and NeI are such as: (a) LTM establishment is a subconscious process; (b) The long-term memory is established during sleeping; (c) The major mechanism for LTM establishment is by sleeping; (d) The general acquisition cycle of LTM is equal to or longer than 24 hours; (e) The mechanism of LTM establishment is to update the entire memory of information represented as an OAR model in the brain; and (f) Dreams and eye movement play an important role in LTM creation. The latest development in CI and NeI has led to the determination of the magnificent and the upper-bound capacity of human memory as described in Section 4.2.

### 3.4. The OAR Model of Information Representation in the Brain

Investigation into the cognitive models of information and knowledge representation in the brain is perceived to be one of the fundamental research areas that help to unveil the mechanisms of the brain. The *Object-Attribute-Relation* (OAR) model [40] describes human memory, particularly the long-term memory, by using the *relational* metaphor, rather than the traditional *container* metaphor that used to be adopted in psychology, computing, and information science. The OAR model shows that human memory and knowledge are represented by relations, i.e. connections of synapses between neurons, rather than by the neurons themselves as the traditional container metaphor suggested. The OAR model can be used to explain a wide range of human information processing mechanisms and cognitive processes.

To rigorously explain the hierarchical and dynamic neural cluster model of memory at neurological and physiological levels, a logical model of memory is needed as given below known as the OAR model.

**Definition 6.** The *OAR model* of LTM can be described as a triple, i.e.:

$$OAR \triangleq (O, A, R) \quad (4)$$

where  $O$  is a finite set of objects identified by unique symbolic names, i.e.:

$$O = \{o_1, o_2, \dots, o_i, \dots, o_n\} \quad (5)$$

For each given  $o_i \in O$ ,  $1 \leq i \leq n$ ,  $A_i$  is a finite set of attributes for characterizing the object, i.e.:

$$A_i = \{A_{i1}, A_{i2}, \dots, A_{ij}, \dots, A_{im}\} \quad (6)$$

where each  $o_i \in O$  or  $A_{ij} \in A_i$ ,  $1 \leq i \leq n$ ,  $1 \leq j \leq m$ , is physiologically implemented by a neuron in the brain.

For each given  $o_i \in O$ ,  $1 \leq i \leq n$ ,  $R_i$  is a set of relations between  $o_i$  and other objects or attributes of other objects, i.e.:

$$R_i = \{R_{i1}, R_{i2}, \dots, R_{ik}, \dots, R_{iq}\} \quad (7)$$

where  $R_{ik}$  is a relation between two objects,  $o_i$  and  $o_{i'}$ , and their attributes  $A_{ij}$  and  $A_{i'j}$ ,  $1 \leq i \leq n$ ,  $1 \leq j \leq m$ , i.e.:

$$\begin{aligned} R_{ik} = & r(o_i, o_{i'}) \\ & | r(o_i, A_{ij}) \\ & | r(A_{ij}, o_{i'}) \\ & | r(A_{ij}, A_{i'j}), 1 \leq k \leq q \end{aligned} \quad (8)$$

To a certain extent, the entire knowledge in the brain can be modeled as a global *OAR* model as illustrated in Fig. 4.

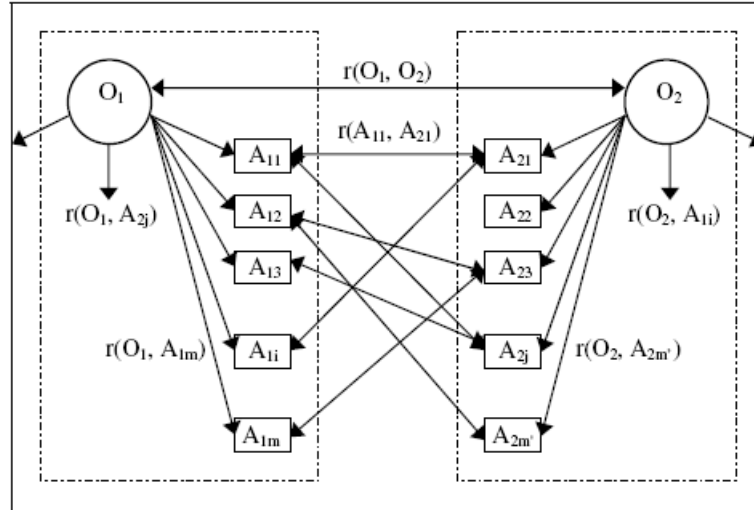


Figure 4. The OAR model of logical memory architectures

### 3.5. A Formal Model of Consciousness and the Perceptual Engines

The studies on consciousness can be traced back as early as to the Aristotelian era, when the durlism treats human beings as the body and soul or the brain and mind problem [9, 15, 19, 28, 62, 65]. Consciousness is the basic characteristic of life and the mind, which is the state of being aware of oneself, of perception to both internal and external worlds, and of responsive to one's surroundings.

**Definition 7.** *Consciousness* is a life function of the sense of self at the perception layer of LRMB, which represents a collective state of the brain's awareness of the internal states and responsive to the external environment.

From the point of computational intelligence view, as the senses of self and of intentionality, consciousness is the entire state of the human system encompassing the internal sates of the brain, internal states of the body, senses about the external environment, interactions (behaviors) between the brain and the body. Therefore, in an analogy, the brain is equivalent to a parallel real-time multi-thread system, which autonomously dispatching conscious and subconscious life functions.

According to the LRMB model, human consciousness is a collective mental state inductively generated or synthesized from the levels of metabolic homeostasis, unconsciousness, subconsciousnes, and consciousness from bottom-up. In other words, consciousness may be deductively analyzed in a top-down approach at these four levels, which helps to explain how consciousness, the sign of life or the seat of intelligence, is created on the basis of biological and physiological foundations.

A formal process model of consciousness can be rigorously described in RTPA as shown in Fig. 5 [62]. In the mathematical model, the conscious process  $\S\text{CSPST}$  is the main base-level processes of

the brain, which switches between the conscious §CSPST and subconscious processes §SCPST in a loop between the states of awake and sleep. During the awake period of a human being, the conscious processes §CSPST may be interrupted by the attention process ATPST when an interrupt @int⊙ is captured by the system consciousness §CSPST.

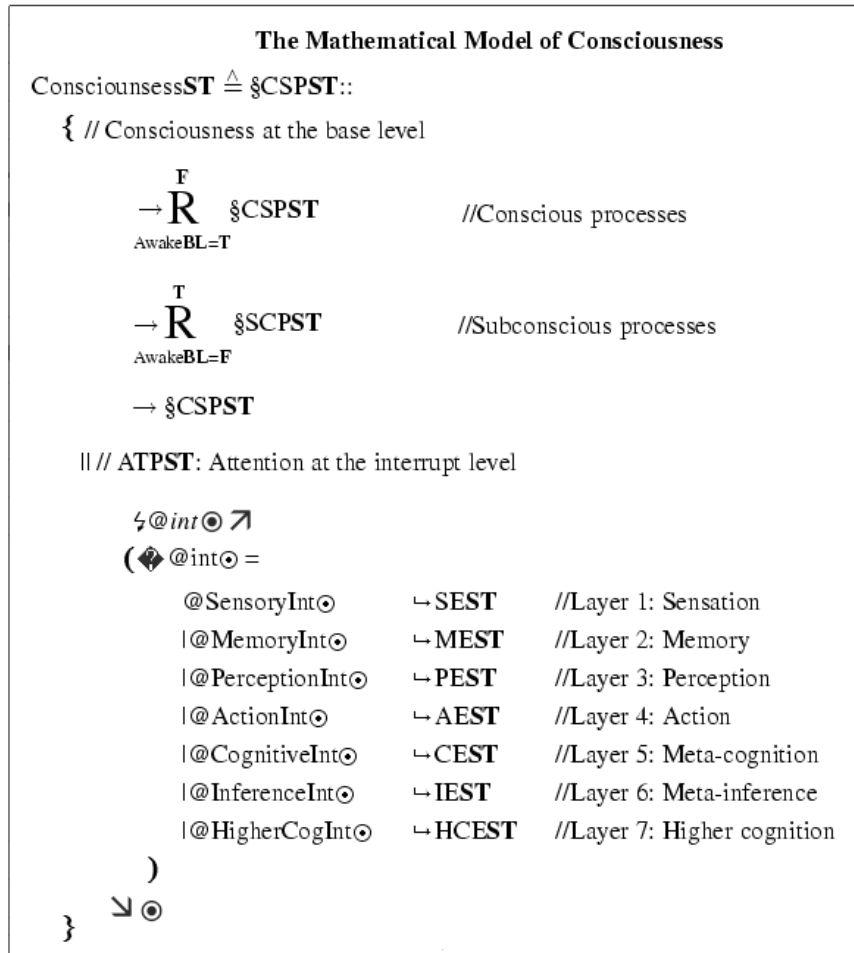


Figure 5. The mathematical model of consciousness in RTPA

### 3.6. A Unified Theory of Human and Machine Learning

Learning is a cognitive process of knowledge and behavior acquisition. A various forms of learning have been identified in psychology such as the classic conditioning learning, supervised learning, latent learning, and social learning on the basis of behaviorism and associationism [19, 27, 29]. Learning is commonly perceived as a process of association of a certain form of object with existing knowledge in the memory of the brain. In cognitive science, learning is deemed as a relatively permanent change in the behavior, thought, and feelings as a consequence of prior experience [10, 12, 24, 25, 27, 65].

In CI, learning [53] is defined as a cognitive process at the higher cognitive function layer according to LRMB. The learning process is interacting with multiple fundamental cognitive processes such as *object identification, abstraction, search, concept establishment, comprehension, memorization, and retrievably testing*.

**Definition 8.** *Learning* is a higher cognitive process of the brain at the higher cognitive layer that gains knowledge of something or acquires skills in some actions or practice, which result in the updating of the cognitive models in LTM.

The physiological foundation for learning is memory, because memory, particularly LTM, contains objects, results, and the context of learning. The most significant result of learning is the change of the cognitive model in LTM as logically modeled by the OAR model presented in Section 3.4. Learning also results in behavioral or capacity changes, while some of them may not be observed immediately or explicitly.

**Theorem 4.** The representation of learning results states that the internal memory in the form of the OAR structure can be updated by a composition between the entire existing OARST and the newly created sub-OAR (sOARST), i.e.:

$$\begin{aligned} OAR'ST &\triangleq OARST \uplus sOARST \\ &= OARST \uplus (O_s, A_s, R_s) \end{aligned} \quad (9)$$

where the composition operation  $\uplus$  on concepts and knowledge is defined below.

**Definition 9.** A *composition* of concept  $c$  from  $n$  subconcepts  $c_1, c_2, \dots, c_n$ , denoted by  $\uplus$ , is an integration of them that creates the new super concept  $c$  via concept conjunction, and establishes new associations between them, i.e.:

$$\begin{aligned} c(O, A, R^c, R^i, R^o) \uplus \biguplus_{i=1}^n c_i &\triangleq \\ c(O, A, R^c, R^i, R^o | O = \bigcup_{i=1}^n O_{c_i}, A = \bigcup_{i=1}^n A_{c_i}, \\ R^c = \bigcup_{i=1}^n (R_{c_i}^c \cup \{(c, c_i), (c_i, c)\}), R^i = \bigcup_{i=1}^n R_{c_i}^i, R^o = \bigcup_{i=1}^n R_{c_i}^o) & \\ || \biguplus_{i=1}^n c_i(O_i, A_i, R_i^c, R_i^{i'}, R_i^{o'} | R_i^{i'} = R_i^i \cup \{(c, c_i)\}, R_i^{o'} = R_i^o \cup \{(c_i, c)\}) & \end{aligned} \quad (10)$$

As specified in Definition 9, the composition operation in concept algebra results in the generation of new internal relations  $\Delta R^c = \bigcup_{i=1}^n \{(c, c_i), (c_i, c)\}$  that are not belongs to any of its subconcepts. It is also noteworthy that, during learning by concept composition, the existing knowledge in forms of the  $n$  individual concepts is changed and updated concurrently via the newly created input/output relations with the newly generated concept.

**Corollary 1.** The *learning process* is a cognitive composition of a piece of newly acquired information and the existing knowledge in LTM in the form of the OAR-based knowledge networks.

Theorem 4 and Corollary 1 explain how existing knowledge is extended or updated based on the OAR model during learning, and how new knowledge is created in OAR in human brains. However, it is noteworthy that knowledge composition based on OAR is an adaptive process that enables new knowledge to be integrated into the existing OAR network in LTM [40].

## 4. Applications of Cognitive Informatics

Sections 2 and 3 have reviewed the latest development of fundamental researches in CI, particularly its theoretical framework and denotational mathematics. A wide range of applications of CI has been identified in multidisciplinary and transdisciplinary areas, which will be described in the following subsections.

### 4.1. Cognitive Computing and Cognitive Computers

Computing systems and technologies can be classified into the categories of *imperative*, *autonomic*, and *cognitive* computing from the bottom up. The imperative computers are a traditional and passive system based on stored-program controlled behaviors for data processing [31]. The autonomic computers are goal-driven and self-decision-driven machines that do not rely on instructive and procedural information [13, 14, 40, 43]. Cognitive computers are more intelligent computers beyond the imperative and autonomic computers, which embody major natural intelligence behaviors of the brain such as thinking, inference, and learning.

**Definition 10.** A *cognitive computer* is an intelligent knowledge processor with the capabilities of autonomous inference and perception that mimics the mechanisms of the brain.

The architectural model of cognitive computers can be refined by a behavioral model that evolves computing technologies from the conventional imperative behaviors to the autonomic and cognitive behaviors.

**Definition 11.** The *behavioral model of a cognitive computer*,  $\S_{CC}$ , is an abstract logical model of computing platform denoted by a set of parallel computing architectures and behaviors as shown in Fig. 6, where  $\parallel$  denotes a parallel relation between given components of the system.

As shown in Fig. 6, the cognitive computer  $\S_{CC}$  is logically abstracted as a set of process behaviors and underlying resources, such as the memory, ports, the system clock, variables, and statuses. A cognitive computer behavior in term of a process  $P_k$  is controlled and dispatched by the system  $\S_{CC}$ , which is triggered by various external or system events and needs, such as interrupts, goals, decisions, perception, and inference. *Cognitive computers* are aimed at cognitive and perceptive *concept/knowledge* processing based on contemporary denotational mathematics. As that of mathematical logic and Boolean algebra are the mathematical foundations of von Neumann architectures, the mathematical foundations of cognitive computers are based on denotational mathematics [46]. According to the LRMB reference model, since all the 39 fundamental cognitive processes of human brains can be formally described in concept algebra and RTPA, they are simulatable and executable by the cognitive computers.

### 4.2. Estimation of the Capacity of Human Memory

Despite the fact that the number of neurons in the brain has been identified in cognitive and neural sciences, the magnitude of human memory capacity is still unknown. According to the OAR model, a recent discovery in CI is that the upper bound of memory capacity of the human brain is in the order of  $10^{8,432}$  bits [58]. The determination of the magnitude of human memory capacity is not only theoretically significant in CI, but also practically useful to unveil the human potential, as well as the gaps between the natural and machine intelligence. This result indicates that the next generation computer memory

$$\begin{aligned}
& \S_{CC} \triangleq \text{Cognitive\_Computer} \mathbf{ST} :: \\
& \{ \text{// System Architectures} \\
& \quad \mathop{\text{<}}_{i \in \mathbf{N}=0}^{n_{proc} \mathbf{N}-1} \mathbf{R} \ P_i \mathbf{ST} \text{>} \quad \text{// Processes} \\
& \quad \mathop{\| \text{<}}_{addr \mathbf{P}=0}^{n_{MEM} \mathbf{H}-1} \mathbf{R} \ \text{MEM}[\text{ptr} \mathbf{P}] \mathbf{RT} \text{>} \quad \text{// Memory} \\
& \quad \mathop{\| \text{<}}_{ptr \mathbf{P}=0}^{n_{PORT} \mathbf{H}-1} \mathbf{R} \ \text{PORT}[\text{ptr} \mathbf{P}] \mathbf{RT} \text{>} \quad \text{// Ports} \\
& \quad \mathop{\| \text{<}} \S \mathbf{TM} \text{>} \quad \text{// The system clock} \\
& \quad \mathop{\| \text{<}}_{i \in \mathbf{N}=0}^{n_v \mathbf{N}-1} \mathbf{R} \ v_i \mathbf{RT} \text{>} \quad \text{// System variables} \\
& \quad \mathop{\| \text{<}}_{i \in \mathbf{N}=0}^{n_s \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{S}}_i \mathbf{BL} \text{>} \quad \text{// System statuses} \\
& \} \\
& \mathop{\| \{ \text{// System Behaviors}} \\
& \quad \mathop{\| \text{<}}_{k \in \mathbf{N}=0}^{n_e \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{e}}_k \mathbf{S} \ \text{\textleftarrow} \mathbf{P}_k \text{>} \quad \text{// Event-driven behaviors } (B_e) \\
& \quad \mathop{\| \text{<}}_{k \in \mathbf{N}=0}^{n_t \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{t}}_k \mathbf{TM} \ \text{\textleftarrow} \mathbf{P}_k \text{>} \quad \text{// Time-driven behaviors } (B_t) \\
& \quad \mathop{\| \text{<}}_{k \in \mathbf{N}=0}^{n_{int} \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{int}}_k \text{\textcircled{O}} \ \text{\textleftarrow} \mathbf{P}_k \text{>} \quad \text{// Interrupt-driven behaviors } (B_{int}) \\
& \quad \mathop{\| \text{<}}_{k \in \mathbf{N}=0}^{n_g \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{g}}_k \mathbf{ST} \ \text{\textleftarrow} \mathbf{P}_k \text{>} \quad \text{// Goal-driven behaviors } (B_g) \\
& \quad \mathop{\| \text{<}}_{k \in \mathbf{N}=0}^{n_d \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{d}}_k \mathbf{ST} \ \text{\textleftarrow} \mathbf{P}_k \text{>} \quad \text{// Decision-driven behaviors } (B_d) \\
& \quad \mathop{\| \text{<}}_{k \in \mathbf{N}=0}^{n_p \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{p}}_k \mathbf{ST} \ \text{\textleftarrow} \mathbf{P}_k \text{>} \quad \text{// Perception-driven behaviors } (B_p) \\
& \quad \mathop{\| \text{<}}_{k \in \mathbf{N}=0}^{n_{inf} \mathbf{N}-1} \mathbf{R} \ \text{\textcircled{inf}}_k \mathbf{ST} \ \text{\textleftarrow} \mathbf{P}_k \text{>} \quad \text{// Inference-driven behaviors } (B_{inf}) \\
& \}
\end{aligned}$$

Figure 6. The mathematical model of cognitive computers

systems may be built according to the OAR model rather than the traditional container metaphor, because the former is more powerful, flexible, and efficient to generate a tremendous memory capacity by using limited number of neurons in the brain or hardware cells in the next generation computers.

It is observed that the total neurons in the brain is about  $n = 10^{11}$  and their *average* synaptic connections is  $s = 10^3$  [11, 20, 24]. According to the relational model of memory, the fundamental question on the capacity of human memory derived in cognitive science and neuropsychology can be reduced to a classical combinatorial problem.

**Theorem 5.** The capacity of human memory  $C_m$  is determined by the total potential relational combinations,  $C_n^s$ , among all neurons  $n = 10^{11}$  and their *average* synaptic connections  $s = 10^3$  to various related subset of entire neurons, i.e.:

$$\begin{aligned} C_m &\triangleq C_n^s \\ &= \frac{10^{11}!}{10^3!(10^{11} - 10^3)!} \\ &\approx 10^{8,432} \text{ [bit]} \end{aligned} \quad (11)$$

Theorem 5 provides a mathematical explanation of the upper limit of the potential number of connections among neurons in the brain. Using approximation theory and a computational algorithm, the solution of Eq. 11 had been successfully obtained as given above [58]. The finding on the magnitude of the human memory capacity on the order as high as  $10^{8,432}$  bits reveals an interesting mechanism of the brain in neural informatics. That is, the brain does not create new neurons to represent new information, instead it generates new synapses between the existing neurons in order to represent new information. The observations in neurophysiology that the number of neurons is kept stable rather than continuously increasing in adult brains provided evidences for the relational cognitive model of information representation in long-term memory.

### 4.3. Cognitive Properties of Knowledge

Almost all modern disciplines of science and engineering deal with information and knowledge. According to CI theories, cognitive information may be classified into four categories known as *knowledge*, *behaviors*, *experience*, and *skills* as shown in Table 2.

Tabela 2. Types of Cognitive Information

		Type of Output		Ways of Acquisition
		Abstract Concept	Empirical Action	
Type of Input	Abstract Concept	Knowledge	Behavior	<i>Direct or indirect</i>
	Empirical Action	Experience	Skill	<i>Direct only</i>

**Lemma 1.** The taxonomy of *cognitive information* is determined by its types of inputs and outputs to and from the brain during learning and information processing, where both inputs and outputs can be either abstract information (concept) or empirical information (actions).

It is noteworthy that the approaches to acquire knowledge behaviors and experiences skills are fundamentally different. The former may be obtained either directly based on hands-on activities or indirectly by reading, while the latter can never be acquired indirectly. According to Lemma 1, the following principle for information manipulation and learning for both human and machine systems can be derived.

**Theorem 6.** The *principle of information acquisition* states that there are four categories of learning objects known as those of knowledge, behaviors, experience, and skills.

Theorem 6 indicates that learning theories and their implementation in autonomic and intelligent systems should study all four categories of cognitive information acquisitions, particularly behaviors,

experience, and skills rather than only focusing on knowledge. Theorem 7 lays an important foundation for learning theories and pedagogy.

**Corollary 2.** All the four categories of cognitive information can be acquired directly by an individual. However, knowledge and behaviors can be learnt indirectly by inputting abstract information; while experience and skills must only be learnt directly by hands-on or empirical actions.

#### 4.4. Simulations of Human Cognitive Behaviors Based on Denotational Mathematics

The contemporary denotational mathematics as described in Section 2.3, particularly concept algebra and RTPA, may be used to simulate the cognitive processes of the brain as modeled in LRMB [60]. Most of the 39 cognitive processes identified in LRMB, such as the learning [53] and reasoning [42] processes, have been rigorously modeled and described in denotational mathematics. Based on the fundamental work, the inference engine and perception engine of a virtual brain can be implemented on cognitive computers or be simulated on conventional computers. In the former case, a working prototype of a fully autonomous computer will be realized on the basis of CI theories and denotational mathematics.

#### 4.5. Cognitive Complexity of Software

The estimation and measurement of functional complexity of software are a highly persistent problem in software engineering. The cognitive complexity of software [38] is a new measurement for cross-platform analysis of complexities, sizes, and comprehension effort of software specifications and implementations in the phases of design, implementation, and maintenance in software engineering. This work reveals that the cognitive complexity of software is a product of its architectural and operational complexities on the basis of deductive semantics and the abstract system theory. Ten fundamental basic control structures (BCS's) are elicited from software architectural/behavioral specifications and descriptions [38]. The cognitive weights of those BCS's are derived and calibrated via a series of psychological experiments. Based on this work, the cognitive complexity of software systems can be rigorously and accurately measured and analyzed. Comparative case studies demonstrate that the cognitive complexity is highly distinguishable in software functional complexity and size measurement in software engineering.

A set of psychological experiments has been carried out in software engineering courses and in the software industry. Based on 126 experiment results, the equivalent cognitive weights of the ten fundamental BCS's are statistically calibrated as summarized in Table 3 [38], where the relative cognitive weight of the sequential structures is assumed one, i.e.  $w_1 = 1$ .

According to *deductive semantics* [37, 50], the complexity of a software system, or its semantic space, is determined not only by the number of operations, but also by the number of data objects.

**Theorem 7.** The *cognitive complexity*  $C_c(S)$  of a software system  $S$  is a product of the operational complexity  $C_{op}(S)$  and the architectural complexity  $C_a(S)$ , i.e.:

$$\begin{aligned}
 C_c(S) &= C_{op}(S) \bullet C_a(S) \\
 &= \left\{ \sum_{k=1}^{n_C} \sum_{i=1}^{\#(C_s(C_k))} w(k, i) \right\} \bullet \left\{ \sum_{k=1}^{n_{CLM}} \text{OBJ}(CLM_k) + \sum_{k=1}^{n_C} \text{OBJ}(C_k) \right\} \quad [\text{FO}] \quad (12)
 \end{aligned}$$

Tabela 3. Calibrated Cognitive Weights of BCS's

BCS	RTPA Notation	Description	Calibrated cognitive weight
1	$\rightarrow$	Sequence	1
2		Branch	3
3	l...l...	Switch	4
4	$R'$	For-loop	7
5	$R^*$	Repeat-loop	7
6	$R^*$	While-loop	8
7	$\rightsquigarrow$	Function call	7
8	$\mathcal{O}$	Recursion	11
9	or $\overline{\overline{\text{ff}}}$	Parallel	15
10	$\Leftarrow$	Interrupt	22

Theorem 7 indicates that the cognitive complexity of a software system is proportional to both its operational and structural complexities. That is, the more the architectural data objects and the higher the operational complicity onto these objects, the larger the cognitive complexity of the system.

Based on Theorem 7, the cognitive complexities of four typical software components [38] have been comparatively analyzed as summarized in Table 4. For enabling comparative analyses, data based on existing complexity measures, such as *time*, *cyclomatic*, and *symbolic* (LOC) complexities, are also contrasted in Table 4.

Tabela 4. Measurement of Software System Complexities

System	Time complexity ( $C_t[OP]$ )	Cyclomatic complexity ( $C_m[-]$ )	Symbolic complexity ( $C_s[LOC]$ )	Cognitive complexity		
				Operational complexity ( $C_{op}[F]$ )	Architectural complexity ( $C_a[O]$ )	Cognitive complexity ( $C_c[FO]$ )
IBS (a)	$\epsilon$	1	7	13	5	65
IBS (b)	$O(n)$	2	8	34	5	170
MaxFinder	$O(n)$	2	5	115	7	805
SIS_Sort	$O(m+n)$	5	8	163	11	1,793

Observing Table 4 it is noteworthy that the first three traditional measurements cannot actually reflect the real complexity of software systems in software design, representation, cognition, comprehension, and maintenance. It is found that: (a) Although four example systems are with similar symbolic complexities, their operational and functional complexities are greatly different. This indicates that the symbolic complexity cannot be used to represent the operational or functional complexity of software systems. (b) The symbolic complexity (LOC) does not represent the throughput or the input size of problems. (c) The time complexity does not work well for a system there is no loops and dominate operations, because

in theory that all statements in linear structures are treated as zero in this measure no matter how long they are. In addition, time complexity cannot distinguish the real complexities of systems with the same asymptotic function, such as in Case 2 (IBS (b)) and Case 3 (Maxfinder). (d) The cognitive complexity is an ideal measure of software functional complexities and sizes, because it represents the real semantic complexity by integrating both the operational and architectural complexities in a coherent measure. For example, the difference between IBS(a) and IBS(b) can be successfully captured by the cognitive complexity. However, the symbolic and cyclomatic complexities cannot identify the functional differences very well.

#### 4.6. Autonomous Agent Systems

**Definition 12.** A *software agent*, or more actually an *intelware*, is an intelligent software system that autonomously carries out robotistic and interactive applications based on goal-driven cognitive mechanisms.

According to Wang's abstract intelligence theory [55], an autonomous software agent is supposed to be called as an *intelligent-ware*, shortly, an *intelware*, parallel to hardware and software in computing, information science, and artificial intelligence. On the basis of Definition 12, an autonomous agent is a software agent that possesses high-level autonomous ability and behaviors beyond conventional imperative computing technologies.

**Definition 13.** An *Autonomous Agent System* (AAS) is a composition of distributed agents that possesses autonomous computing and decision making abilities as well as interactive communication capability to peers and the environment.

Despite the fact that the origin of software agent systems has been rooted in autonomous artificial intelligence and cognitive psychology, their implementations are still based on conventional imperative computing techniques rather than autonomous computational intelligence. A *hierarchical reference model* of Autonomous Agent Systems (AAS's) is developed [56], which reveals that an autonomous agent possesses intelligent behaviors at three layers known as those of imperative, autonomic, and autonomous from the bottom up. The theoretical framework of AAS's is described from the facets of cognitive informatics, computational intelligence, and denotational mathematics.

**Theorem 8.** The relationships of the *imperative* behaviors  $B_I$ , *autonomic* behaviors  $B_C$ , and *cognitive* behaviors  $B_A$  of intelware or AAS's are hierarchical and inclusive, i.e.:

$$B_I \subseteq B_C \subseteq B_A \quad (13)$$

Theorem 8 and Definition 13 indicate that any lower layer behavior of an intelware or AAS is a subset of those of a higher layer. In other words, any higher layer behavior is a natural extension of those of lower layers as shown in Fig. 1. Therefore, the *necessary and sufficient conditions of AAS's*,  $C_{AAS}$ , are the possession of all behaviors at the three layers.

Because a software agent may be perceived as an application-specific virtual brain, behaviors of an autonomous agent are mirrored human behaviors. The fundamental characteristics of agent-based systems are autonomic computing, goal-driven action-generation, knowledge-based machine learning. The LRMB model [60] described in Section 3.3 may be used as a reference model for agent-based technologies. This is a fundamental view toward the formal description and modeling of architectures

and behaviors of agent systems, which are created to do something repeatable in context, to extend human capability, reachability, and/or memory capacity. It is found that both human and software behaviors can be described by a 3-dimensional representative model comprising *action*, *time*, and *space*. For agent system behaviors, the three dimensions are known as *mathematical operations*, *event/process timing*, and *memory manipulation* [38]. The 3-D behavioral space of agents can be formally described by RTPA that serves as an expressive mathematical means for describing thoughts and notions of dynamic system behaviors as a series of actions and cognitive processes.

#### 4.7. Inferential Modeling Techniques

An inferential model was proposed for classification of knowledge types in industrial problem solving [4], which is applied to tackle issues of cognitive informatics for problem solving in engineering domains. The inferential model provides a “high level content theory” [21] for guiding knowledge acquisition and analysis in the development of knowledge-based systems. An Inferential Modeling Technique (IMT) is derived for analyzing knowledge in diverse domains including a legal domain [5], a reforestation domain [6], and a petroleum engineering domain [7, 8].

The inferential model extends the traditional domain, inference, task, and strategy knowledge as in the KADS expertise model to meta-linguistic properties that may be preserved including coherence, relevance, necessity, normality and abnormality of function inputs and outputs. The extension concerns the strategy to be used for accomplishing a task. Each task is performed to achieve some goal, and the strategic knowledge specifies what goal or task the system should attempt in response to some typically external conditions. This knowledge often consists of criteria or preference parameters. It refers to the underlying or implicit assumptions, which affect trade-off decisions the expert makes in a real world context. For example, the preference parameters of “cost”, “risk”, and “importance of task” may be the criteria for prioritizing a sequence of tasks or activities. In clarifying strategic knowledge, the knowledge engineer and expert are forced to communicate on the implicit notions, which explain the priorities in the ordering of the task structures derived from the nature of the problem domain. Sometimes strategic knowledge is embedded in the ordering of activities in a task structure and not explicitly represented in the system.

#### 4.8. Cognitive Network and Machine Learning

Networked computers reside at the heart of systems on which people now rely, both in critical national infrastructures and in private enterprises. Many of these systems are far too vulnerable to cyber attacks that can inhibit their functioning, corrupt important data, or expose private information. It is extremely important to make the system resistant to and tolerant of these cyber attacks.

Machine learning is the study of how to build computer programs that improve their performance through experience. Machine learning algorithms have proven to be of great practical value in a variety of application domains. To meet the challenge of developing and maintaining larger and complex software systems in a dynamic and changing environment, Zhang and Tsai [74, 75, 76] have studied the applications of machine learning methods to software development and maintenance tasks. Tsai and Yu [30] have investigated the applications of machine learning in security, reliability, and privacy of cyber-based systems.

An Intrusion Detection System (IDS) is a security layer to detect ongoing intrusive activities in information systems. Traditionally, intrusion detection relies on extensive knowledge of security experts, in particular on their familiarity with the computer system to be protected. To reduce this dependency, various data mining and machine learning techniques have been deployed for intrusion detection. An intrusion detection system is usually working in a dynamically changing environment, which forces continuous tuning of the intrusion detection model, in order to maintain sufficient performance. The manual tuning process required by current systems depends on the system operators to work out the tuning solution and to integrate it into the detection model. Yu and Tsai [67, 68, 69] presented an automatically tuning intrusion detection system (ATIDS) using learning algorithm and neural networks for intrusion detection. ATIDS automatically tunes the detection model on the fly according to the feedback provided by the system operator when false predictions are encountered. ATIDS was evaluated using the KDDCup'99 intrusion detection dataset. Experimental results show that the system achieves up to 35% improvement in terms of misclassification cost when compared with a system lacking the turning feature.

## 5. Conclusions

Cognitive informatics (CI) has been presented as a transdisciplinary enquiry of cognitive and information sciences that investigates into the internal information processing mechanisms and processes of the brain and natural intelligence, and their engineering applications via an interdisciplinary approach. This paper has provided an insightful perspective on the past, present, and future of CI, which reviews the development of informatics from the classical information theory, contemporary informatics, to cognitive informatics. Based on this, the fundamental theories of cognitive informatics and its applications have been explored. Cognitive informatics has been described as a profound interdisciplinary research area that tackles the common root problems of modern informatics, computation, software engineering, AI, cognitive science, neuropsychology, computational intelligence, and life sciences. A wide range of applications of CI has been identified in multidisciplinary and transdisciplinary areas, such as the architecture of future generation computers known as the cognitive computers, explanation of human memory mechanisms and capacity, cognitive properties of information, data, knowledge, and skills in knowledge engineering, simulation of human cognitive behaviors using descriptive mathematics, development of autonomous agent systems, studies on the CI foundations of software engineering, cognitive complexity of software systems, and the implementation of autonomous machine learning systems.

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