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Article *in* International Journal of Software Science and Computational Intelligence · February 2007

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On Abstract Intelligence: Toward a Unifying Theory of Natural, Artificial, Machinable, and Computational Intelligence

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ABSTRACT

Abstract intelligence is a human enquiry of both natural and artificial intelligence at the reductive embodying levels of neural, cognitive, functional, and logical from the bottom up. This paper describes the taxonomy and nature of intelligence. It analyzes roles of information in the evolution of human intelligence, and the needs for logical abstraction in modeling the brain and natural intelligence. A formal model of intelligence is developed known as the Generic Abstract Intelligence Mode (GAIM), which provides a foundation to explain the mechanisms of advanced natural intelligence such as thinking, learning, and inferences. A measurement framework of intelligent capability of humans and systems is comparatively studied in the forms of intelligent quotient, intelligent equivalence, and intelligent metrics. On the basis of the GAIM model and the abstract intelligence theories, the compatibility of natural and machine intelligence is revealed in order to investigate into a wide range of paradigms of abstract intelligence such as natural, artificial, machinable intelligence, and their engineering applications.

Keywords: *AI; brain science; cognitive models; cognitive processes; concept algebra; denotational mathematics; GAIM; intelligent measurement; intelligent metrics; intelligence science; intelligent quotient; LRMB; mathematical models; OAR; RTPA*

INTRODUCTION

Intelligence is a driving force or an ability to acquire and use knowledge and skills, or to inference in problem solving. It is a profound human wonder on how conscious intelligence is generated as a highly complex cognitive state in human mind on the basis of biological and physiological structures. How natural intelligence functions logically and physiologi-

cally? How natural and artificial intelligence are converged on the basis of brain, software, and intelligence science? It was conventionally deemed that only mankind and advanced species possess intelligence. However, the development of computers, robots, software agents, and autonomous systems indicates that intelligence may also be created or embodied by machines and man-made systems. Therefore, it is one of the key objectives in cognitive informatics and

intelligence science to seek a coherent theory for explaining the nature and mechanisms of both natural and artificial intelligence.

The history of investigation into the brain and natural intelligence is as long as the history of mankind, which can be traced back to the Aristotle's era and earlier. Early studies on intelligence are represented by works of Vygotsky, Spearman, and Thurstone (Bender, 1996; Matlin, 1998; Payne and Wenger, 1998; Parker and McKinney, 1999; Wilson and Keil, 2001; Lefton et al., 2005). Lev Vygotsky's (1896 - 1934) presents a communication view that perceives intelligence as inter- and intra-personal communication in a social context. Charles E. Spearman (1863 - 1945) and Lois L. Thurstone (1887 - 1955) proposed the *factor theory* (Lefton et al., 2005), in which seven factors of intelligence are identified such as the *verbal comprehension, word fluency, number facility, spatial visualization, associative memory, perceptual speed, and reasoning*.

David Wechsler's *intelligent measurement theory* (Lefton et al., 2005) models intelligence from the aspects of *verbal, quantitative, abstract visual, and short-term working memory reasoning*. He proposed the Wechsler Adult Intelligence Scale (WAIS) in 1932. Arthur Jensen's *two-level theory* (Jensen, 1969, 1970, 1987) classifies intelligence into two levels known as the *associative ability level* and the *cognitive ability level*. The former is the ability to process external stimuli and events; while the latter is the ability to carry out reasoning and problem solving.

Howard Gardner's *multiple intelligences theory* (Gardner, 1983, 1995) identifies eight forms of intelligence, which are those of *linguistic, logical-mathematical, musical, spatial, bodily-kinaesthetic, naturalist, interpersonal, and intrapersonal*. He perceives that intelligence is an ability to solve a problem or create a product within a specific cultural setting. Robert J. Sternberg's *triarchic theory* (Sternberg, 1997, 2000, 2003) models intelligence in three dimensions known as the *analytic, practical, and creative* intelligence. He perceives intelligence as the ability to adapt to, shape, and

select environments to accomplish one's goals and those of society. Lester A. Lefton and his colleagues (Lefton et al., 2005) defined intelligence as the overall capacity of the individual to act purposefully, to think rationally, and to deal effectively with the social and cultural environment. They perceive that intelligence is not a thing but a process that is affected by a person's experiences in the environment.

J. McCarthy, M.L. Minsky, N. Rochester, and C.E. Shannon proposed the term *Artificial Intelligence* (AI) in 1955 (McCarthy et al., 1955; McCulloch, 1965). S.C. Kleene analyzed the relations of automata and nerve nets (Kleene, 1956), and Bernard Widrow initiated the technology of *Artificial Neural Networks* (ANNs) in the 1950s (Widrow and Lehr, 1990) based on multilevel, distributed, dynamic, interactive, and self-organizing nonlinear networks (Albus, 1991; Ellis and Fred, 1962; Haykin, 1998). The concepts of robotics (Brooks, 1970) and expert systems (Giarrantans and Riley, 1989) were developed in the 1970s and 1980s, respectively. Then, intelligent systems (Meystel and Albus, 2002) and software agents (Hewitt, 1977; Jennings, 2000) emerged in the 1990s.

Yingxu Wang's *real-time intelligent theory* (Wang, 2007a, 2007b; Wang and Wang, 2006; Wang et al., 2006) reveals that natural intelligence is the driving force that transforms cognitive information in the forms of data, knowledge, skill, and behavior. Intelligence can be modeled into two categories known as the *subconscious* (inherent) intelligence and *conscious* (acquired) intelligence. A *Layered Reference Model of the Brain* (LRMB) has been developed (Wang et al., 2006), which 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.

Cognitive informatics (Wang, 2002a, 2003a, 2006b, 2007b) adopts a compatible perspective on natural and artificial intelligence (Wang, 2007d, 2008d). It is logical to perceive that natural intelligence should be fully understood before artificial intelligence can be scientifically studied. In this view, conven-

tional machines are invented to extend human physical capability, while modern information processing machines such as computers, communication networks, and robots are developed for extending human intelligence, memory, and the capacity of information processing (Wang, 2006a, 2007b). Any machine that may implement a part of human behaviors and actions in information processing has possessed some extent of intelligence. This holistic view has led to the theory of *abstract intelligence* (Wang, 2008c) in order to unify all paradigms of intelligence such as natural, artificial, machinable, and computational intelligence.

This article reveals that abstract intelligence is a form of driving force which transfers information into behaviors or actions. The taxonomy and nature of intelligence is described and roles of information in the evolution of human intelligence and the need for logical abstraction in modeling the brain and natural intelligence are analyzed. A Generic Abstract Intelligence Mode (GAIM) is formally developed, which provides a foundation to explain the mechanisms of advanced natural intelligence such as thinking, learning, and inference. A measurement framework of intelligent capability of humans and systems is presented covering intelligent quotient, intelligent equivalence, and intelligent metrics. Then, the compatibility of nature and machine intelligence is formally established, which forms a theoretical foundation for more rigorous study in natural, artificial, machinable, and computational intelligence as well as their engineering applications.

THE COGNITIVE INFORMATICS FOUNDATIONS OF ABSTRACT INTELLIGENCE

Intelligence plays a central role in cognitive informatics, computing, software science, brain science, and knowledge science. However, it was perceived diversely from different facets. A key in the study of natural and artificial intelligence is the relationships between *infor-*

mation, knowledge, and behavior. Therefore, the nature of intelligence is an ability *to know* and *to do* possessed by both human brains and man-made systems.

In this view, the major objectives of cognitive, software, and intelligence sciences are to answer:

- How the three forms of cognitive entities, i.e., information, knowledge, and behavior, are transformed in the brain or a system?
- What is the driving force to enable these transmissions?

A set of fundamental theories toward modeling and explaining the abstract intelligence has been developed in cognitive informatics, such as the Layered Reference Model of the Brain (LRMB) (Wang et al., 2006) and the OAR model (Wang, 2007c), which play important roles in exploring the abstract intelligence and its real-world paradigms.

Taxonomy of Cognitive Information in the Brain

Almost all modern disciplines of sciences and engineering deal with information and knowledge. However, data, information, and knowledge are conventionally considered as different entities in the literature (Debenham, 1989; Wilson and Keil, 2001). It is perceived that *data* are directly acquired raw information, usually a quantitative abstraction of external objects and/or their relations. *Information*, in a narrow sense, is meaningful data or a subjective interpretation of data. Then, *knowledge* is the consumed information or data related to existing knowledge in the brain.

Based on the investigations in cognitive informatics, particularly the research on the Object-Attribute-Relation (OAR) model (Wang, 2007c) and the mechanisms of internal information representation, the empirical classification of the cognitive hierarchy of data, information, and knowledge may be revised. A cognitive informatics theory on the relationship among data (sensational inputs), actions (behav-

ioral outputs), and their internal representations such as knowledge, experience, behavior, and skill, are that all of them are different forms of cognitive information, which may be classified on the basis of how the internal information relates to the inputs and outputs of the brain as shown in Table 1.

According to Table 1, the taxonomy of cognitive information is determined by types of inputs and outputs of information to and from the brain, where both inputs and outputs can be either information or action. For a given cognitive process, if both I/O are abstract information, the internal information acquired is *knowledge*; if both I/O are empirical actions, the type of internal information is *skill*; and the remainder combinations between action/information and information/action produce *experience* and *behaviors*, respectively. It is noteworthy in Table 1 that behavior is a new type of cognitive information modeled inside the brain, which embodies an abstract input to an observable behavioral output (Wang, 2007b).

Definition 1. *The Cognitive Information Model (CIM) classifies internal information in the brain into four categories, according to their types of I/O information, known as knowledge (K), behavior (B), experience (E), and skill (S), i.e.:*

- a) Knowledge $K: I \rightarrow I$ (1)
 b) Behavior $B: I \rightarrow A$ (2)
 c) Experience $E: A \rightarrow I$

- d) Skill $S: A \rightarrow A$ (3)
 (4)

where I and A represent information and action, respectively.

The approaches to acquire knowledge/behavior and experience/skills are fundamentally different. Although knowledge or behaviors may be acquired directly and indirectly, skills and experiences can only be obtained directly by hands-on activities. Further, the associated memories of the abstract information are different, where knowledge and experience are retained as abstract relations in Long-Term Memory (LTM), while behaviors and skills are retained as wired neural connections in Action Buffer Memory (ABM) (Wang, 2007b, 2008h).

Roles of Information in the Evolution of Natural Intelligence

The profound uniqueness of the discipline of cognitive informatics, software science, and intelligence science lies on the fact that its objects under study are located in a dual world as described below.

Definition 2. *The general worldview, as shown in Figure 1, reveals that the natural world (NW) is a dual world encompassing both the physical (concrete) world (PW) and the abstract (perceived) world (AW).*

Theorem 1. *The Information-Matter-En-*

Table 1. The cognitive information model (CIM)

		Type of output		Ways of acquisition
		Information	Action	
Type of input	Information	Knowledge (K)	Behavior (B)	Direct or indirect
	Action	Experience (E)	Skill (S)	Direct only

ergy-Intelligence (IME-I) model states that the natural world (NW) which forms the context of human and machine intelligence is a dual: one facet of it is the physical world (PW), and the other is the abstract world (AW), where intelligence (\mathfrak{I}) plays a central role in the transformation between information (I), matter (M), and energy (E).

According to the IME-I model, information is the general model for representing 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 (Wang, 2007a). For the former, the gene pools are adopted 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 information and knowledge of collectively cumulated by mankind.

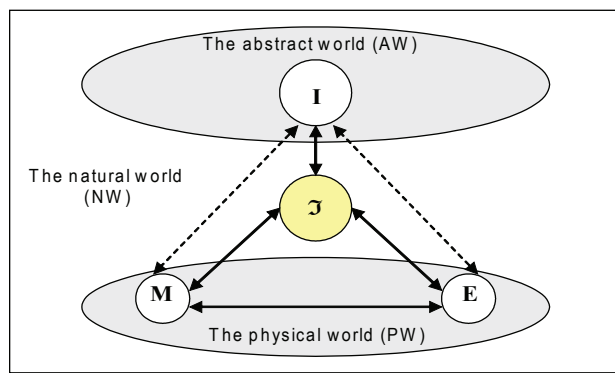
Corollary 1. *Intelligence plays an irreplaceable role in the transformation between information, matter, and energy according to the IME-I model.*

It is observed that almost all cells in human body have a certain lifecycle in which they reproduce themselves via divisions. This

mechanism allows human trait information to be transferred to offspring through gene (DNA) replications during cell reproduction. However, it is observed that the most special mechanism of neurons in the brain is that they are the only type of cells in human body that does not go through reproduction but remains alive throughout the entire human life (Thomas, 1974; Fried and Hademenos, 1999; Kandel et al., 2000). The advantage of this mechanism is that it enables the physiological representation and retention of acquired information and knowledge to be memorized permanently in long-term memory. But the vital disadvantage of this mechanism is that it does not allow acquired information to be physiologically passed on to the next generation, because there is no DNA replication among memory neurons.

This physiological mechanism of neurons in the brain explains not only the foundations of memory and memorization, but also the wonder why acquired information and knowledge cannot be passed and inherited physiologically through generation to generation. Therefore, to a certain extent, mankind relies very much on information for evolution than that of genes, because the basic characteristic of the human brain is intelligent information processing. In other words, the intelligent ability to cumulate and transfer information from generation to generation plays the vital role in mankind's evolution for both individuals and the species.

Figure 1. The IME-I model of the general worldview



This distinguishes human beings from other species in natural evolution, where the latter cannot systematically pass acquired information from generation to generation in order to grow their information/knowledge-bases cumulatively and exponentially (Wang, 2008g).

The Need for Logical Abstraction in Modeling the Brain and Abstract Intelligence

According to the functional model of the brain (Wang and Wang, 2006), genomes may only explain things at the level of *inherited* life functions, rather than that of *acquired* life functions, because the latter cannot be directly represented in genomes in order to be inherited. Therefore, high-level cognitive functional models of the brain are yet to be sought to explain the fundamental mechanisms of the abstract intelligence.

In recent genome research people expect that the decoding and probing of human genomes will solve almost all problems and answer almost all questions about the myths of the natural intelligence. Although the aim is important and encouraging, computer and software scientists would doubt this promising prediction. This is based on the basic reductionism of science and the following observations: Although the details of computer circuitry are fully observable at the bottom level, i.e., at the gate or even the molecular level, seeing computers only as the low-level structures would not help explaining the mechanisms of computing rather than get lost in an extremely large number of interconnected similar elements, if the high-level functional architectures and logical mechanisms of computers were unknown.

Corollary 2. *The principle of functional reductionism states that a logical model of the natural intelligence is needed in order to formally explain the high-level mechanisms of the brain on the basis of observations at the biological and physiological levels.*

The logical model of the brain is the

highest level of abstraction for explaining its cognitive mechanisms. Based on it, a systematical investigation from the levels of logical, functional, physiological, and biological may be established in both the top-down and bottom-up approaches, which will enable the establishment of a coherent theory of abstract intelligence and brain science.

A FORMAL MODEL OF ABSTRACT INTELLIGENCE

Based on the principle of *functional reductionism*, a logical model of the general form of intelligence is needed, known as the abstract intelligence, in order to formally explain the high-level mechanisms of the brain on the basis of observations at the biological, physiological, functional, and logical levels. On the basis of the logical model of abstract intelligence, the studies on the paradigms of abstract intelligence, such as natural, artificial, machinable, and computational intelligence, may be unified into a common framework as developed in cognitive informatics (Wang, 2002a, 2003a, 2007a, 2007b).

Abstract Intelligence and Its Paradigms

Definition 3. *Abstract intelligence, αI , is a human enquiry of both natural and artificial intelligence at the embody levels of neural, cognitive, functional, and logical from the bottom up.*

In the *narrow sense*, αI is a human or a system ability that transforms information into behaviors. While, in the *broad sense*, αI is any human or system ability that autonomously transfers the forms of abstract information between *data*, *information*, *knowledge*, and *behaviors* in the brain or systems.

With the clarification of the intension and extension of the concept of αI , its paradigms or concrete forms in the real-world can be derived

as summarized in Table 2.

Definition 4. *Natural intelligence (NI) is an embodying form of αI that implements intelligent mechanisms and behaviors by naturally grown biological and physiological organisms such as human brains and those of other well developed species.*

Definition 5. *Artificial intelligence (AI) is an embodying form of αI that implements intelligent mechanisms and behaviors by cognitively-inspired artificial models and man-made systems such as intelligent systems, knowledge systems, decision-making systems, and distributed agent systems.*

Definition 6. *Machinable intelligence (MI) is an embodying form of αI that implements intelligent mechanisms and behaviors by complex machine and circuit systems such as computers, robots, circuits, neural networks, and autonomic*

mechanical machines.

Definition 7. *Computational intelligence (CoI) is an embodying form of αI that implements intelligent mechanisms and behaviors by computational methodologies and software systems.*

Typical paradigms of CoI are expert systems, fuzzy systems, autonomous computing, intelligent agent systems, genetic/evolutionary systems, and autonomous learning systems (Jordan, 1999).

Definition 8. *The behavioral model of consciousness, $\S CS\text{-}BST$, is an abstract logical model denoted by a set of parallel processes that encompasses the imperative intelligence \mathfrak{I}_p , autonomic intelligence \mathfrak{I}_A , and cognitive intelligence \mathfrak{I}_C from the bottom-up, i.e. Box 1.*

According to Definition 8, the relation-

Table 2. Taxonomy of abstract intelligence and its embodying forms

No.	Form of intelligence	Embodying Means	Paradigms
1	Natural intelligence (NI)	Naturally grown biological and physiological organisms	Human brains and brains of other well developed species
2	Artificial intelligence (AI)	Cognitively-inspired artificial models and man-made systems	Intelligent systems, knowledge systems, decision-making systems, and distributed agent systems
3	Machinable intelligence (MI)	Complex machine and wired systems	Computers, robots, autonomic circuits, neural networks, and autonomic mechanical machines
4	Computational intelligence (CoI)	Computational methodologies and software systems	Expert systems, fuzzy systems, autonomous computing, intelligent agent systems, genetic/evolutionary systems, and autonomous learning systems

Box 1.

$$\begin{aligned}
 \S CS\text{-}BST &\triangleq (\mathfrak{I}_I, \mathfrak{I}_A, \mathfrak{I}_C) \\
 &= \{ (B_e, B_i, B_{int}) \quad // \mathfrak{I}_I - \text{Imperative intelligence} \\
 &\quad \parallel (B_e, B_i, B_{int}, B_g, B_d) \quad // \mathfrak{I}_A - \text{Autonomic intelligence} \\
 &\quad \parallel (B_e, B_i, B_{int}, B_g, B_d, B_p, B_{inf}) \quad // \mathfrak{I}_C - \text{Cognitive intelligence} \\
 &\quad \}
 \end{aligned}
 \tag{5}$$

ship among the three-form intelligence is as follows:

$$\mathfrak{I}_I \subseteq \mathfrak{I}_A \subseteq \mathfrak{I}_C \quad (6)$$

Both Eqs. 5 and 6 indicate that any lower layer intelligence and behavior is a subset of those of a higher layer. In other words, any higher layer intelligence and behavior is a natural extension of those of lower layers.

The Generic Abstract Intelligence Model (GAIM)

On the basis of the conceptual models developed in previous subsections, the mechanisms of αI can be described by a Generic Abstract Intelligence Model (GAIM) as shown in Figure 2.

In the GAIM model as shown in Figure 2, different forms of intelligence are described as a driving force that transfers between a pair of abstract objects in the brain such as *data* (D), *information* (I), *knowledge* (K), and *behavior* (B). It is noteworthy that each abstract object is physically retained in a particular type of memories. This is the neural informatics foundation of natural intelligence, and the physiological evidences of why natural intelligence can be classified into four forms as given in the following theorem.

Theorem 2. *The nature of intelligence states that abstract intelligence αI can be classified into four forms called the perceptive intelli-*

gence \mathfrak{I}_p , cognitive intelligence \mathfrak{I}_c , instructive intelligence \mathfrak{I}_i , and reflective intelligence \mathfrak{I}_r , as modeled below:

$$\begin{aligned} \alpha I &\triangleq \mathfrak{I}_p : D \rightarrow I \text{ (Perceptive)} \\ || \mathfrak{I}_c &: I \rightarrow K \text{ (Cognitive)} \\ || \mathfrak{I}_i &: I \rightarrow B \text{ (Instructive)} \\ || \mathfrak{I}_r &: D \rightarrow B \text{ (Reflective)} \end{aligned} \quad (7)$$

According to Definition 8 and Theorem 2 in the context of the GAIM model, the narrow sense of αI is corresponding to the instructive and reflective intelligence; while the broad sense of αI includes all four forms of intelligence, that is, the perceptive, cognitive, instructive and reflective intelligence.

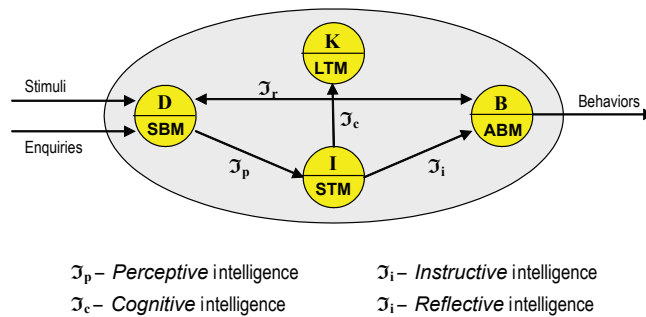
The four abstract objects in Theorem 2 can be rigorously described in the following definitions.

Definition 9. *The abstract object data D in GAIM is a quantitative representation of external entities by a function r_d that maps external message or signal M into a specific measurement scale S_k , i.e.:*

$$\begin{aligned} D &\triangleq r_d : M \rightarrow S_k \\ &= \log_k M, k_{\min} = 2 \end{aligned} \quad (8)$$

where k is the base of the measurement scale,

Figure 2. The generic abstract intelligence model (GAIM)



and the minimum of k , k_{min} , is 2.

Definition 10. The abstract object information I in GAİM in the narrow sense is a perceptive interpretation of data by a function r_i that maps the data into a concept C , i.e.:

$$I \triangleq r_i : D \rightarrow C, r_i \in \mathfrak{R}_{CA} \quad (9)$$

where \mathfrak{R}_{CA} is the nine compositional operations of concepts as defined in concept algebra, $\mathfrak{R}_{CA} = \{\Rightarrow, \Rightarrow^+, \Rightarrow^-, \Rightarrow^{\sim}, \uplus, \uplus, \Leftarrow, \vdash, \rightarrow\}$, with C as a concept in the form given below (Wang, 2008a, 2008b).

Definition 11. An abstract concept c is a 5-tuple, i.e.:

$$c \triangleq (O, A, R^c, R^i, R^o) \quad (10)$$

where

- O is a finite nonempty set of object of the concept, $O = \{o_p, o_{2'}, \dots, o_m\} \subseteq \mathbb{P}E$, where $\mathbb{P}E$ denotes a power set of the universal entities in the discourse of concept environment Θ .
- A is a finite nonempty set of attributes, $A = \{a_p, a_{2'}, \dots, a_n\} \subseteq \mathbb{P}M$, where M is the universal set of attributes of Θ .
- $R^c \subseteq O \times A$ is a finite nonempty set of internal relations.
- $R^i \subseteq A' \times A$, $A' \sqsubseteq C' \wedge A \sqsubseteq c$, is a finite nonempty set of input relations, where C' is a set of external concepts, $C' \sqsubseteq \Theta$, and \sqsubseteq denotes that a set or structure (tuple) is a substructure or derivation of another structure. For convenience, $R^i = A' \times A$ may be simply denoted as $R^i = C' \times c$.
- $R^o \subseteq c \times C'$ is a finite nonempty set of output relations.

Definition 12. The abstract object knowledge K in the brain is a perceptive representation of information by a function r_k that maps a given concept C_0 into all related concepts, i.e.:

$$K \triangleq r_k : C_0 \rightarrow (\bigtimes_{i=1}^n C_i), r_k \in \mathfrak{R}_{CA} \quad (11)$$

Definition 13. The entire knowledge \mathfrak{K} is represented by a concept network, which is a hierarchical network of concepts interlinked by the set of nine associations \mathfrak{R}_{CA} defined in concept algebra, i.e.:

$$\mathfrak{K} = \mathfrak{R} : \bigtimes_{i=1}^n C_i \rightarrow \bigtimes_{j=1}^n C_j \quad (12)$$

Definition 14. The abstract objects behavior B in the brain is an embodied motivation M by a function r_b that maps a motivation M into an executable process P , i.e.:

$$\begin{aligned} B &\triangleq r_b : M \rightarrow P \\ &= \bigtimes_{k=1}^m (@e_k \hookrightarrow P_k) \\ &= \bigtimes_{k=1}^m [@e_k \hookrightarrow \bigtimes_{l=1}^{n-1} (p_i(k) r_{ij}(k) p_j(k))], j \\ &= i+1, r_{ij} \in \mathfrak{R}_{RTPA} \end{aligned} \quad (13)$$

where M is generated by external stimuli or events and/or internal emotions or willingness, which are collectively represented by a set of events $E = \{e_p, e_{2'}, \dots, e_m\}$.

In Definition 14, P_k is represented by a set of cumulative relational subprocesses $p_i(k)$. Mathematical model of the cumulative relational processes may be referred to (Wang, 2008d).

Consciousness of Abstract Intelligence: The Platform of Mind and Thought

The theory of αI may be used to explain how consciousness is generated as a highly complex cognitive state in human mind on the basis of biological and physiological structures. From

a point of view of cognitive informatics, consciousness is the entire state of a human being and his/her environment encompassing the internal states of the brain, internal states of the body, senses about the external environment, interactions (behaviors) between the brain and the body (Wang and Wang, 2006). Therefore, the brain is logically equivalent to a real-time system, and consciousness is logically equivalent to a real-time multi-thread operating system.

On the basis of the cognitive informatics model of the brain, the following analogies show interesting relations between the brain and computing in computational intelligence and software science:

$$\text{Brain} : \text{Mind} = \text{Hardware} : \text{Software} \quad (14)$$

$$\begin{aligned} \text{Consciousness} : \text{Behaviors} \\ = \text{Operating system (NI-OS)} : \text{Applications (NI-App)} \end{aligned} \quad (15)$$

where NI-OS and NI-App denote natural intelligence operating system and applications, respectively.

A process model of consciousness as an NI-OS system can be described in Real-Time ProcessAlgebra (RTPA) (Wang, 2002b, 2003b, 2006a, 2008d, 2008e) as shown in Figure 3. The consciousness process $\S\text{CS}\mathbf{ST}$ is divided into two parts known as the architectural model and the behavioral model of consciousness.

Definition 15. *The architectural model of consciousness, $\S\text{CS-AST}$, is a logical model of the brain in term of the $\text{NI-OS}\mathbf{ST}$, which is denoted by a set of parallel intelligent engines, such as the Sensory Engine (SE), Memory Engine (ME), Perception Engine (PE), Action Engine (AE), Meta-Cognition Engine (CE), Meta-Inference Engine (IE), and Higher Cognition Engine (HCE), from the bottom up according to LRMB, i.e.:*

$$\begin{aligned} \S\text{CS-AST} \triangleq & \text{SE} \quad // \text{Sensory engine} \\ & || \text{ME} \quad // \text{Memory engine} \\ & || \text{PE} \quad // \text{Perception engine} \\ & || \text{AE} \quad // \text{Action engine} \\ & || \text{CE} \quad // \text{Cognitive engine} \\ & || \text{IE} \quad // \text{Inference engine} \\ & || \text{HCE} \quad // \text{Higher cognitive engine} \end{aligned} \quad (16)$$

where $||$ denotes the parallel relation between given components of the system.

In Definition 15, each intelligent engine of $\S\text{CS-AST}$ is further refined by detailed structures and functions as given in Figure 3. In addition, a relative system clock $\S\text{tm}$ is provided in $\S\text{CS-AST}$ for synchronizing dispatching activities and behaviors in the natural intelligence system. The behavioral model of consciousness has been given in Definition 8. Detailed models of each behavior in the categories of imperative, autonomic, and cognitive intelligence are presented in the last section of the $\text{CSP}\mathbf{ST}$ model in Figure 3.

MEASUREMENT OF INTELLIGENCE

On the basis of the formal models of abstract intelligence as developed in previous sections, measurement of intelligence studies how intelligence may be quantified and rigorously evaluated and benchmarked. The measurement of intelligent ability of humans and systems can be classified into three categories known as *intelligent quotient*, *intelligent equivalence*, and *intelligent metrics*.

Intelligent Quotient

The first measurement for mental intelligence is proposed in psychology known as the intelligent quotient based on the *Stanford-Binet intelligence test* (Binet, 1905; Terman and Merrill, 1961). Intelligent quotient is determined by six subtests where the pass of each subtest

is count for two equivalent months of mental intelligence.

Definition 16. *The mental age A_m in an intelligent quotient test is the sum of a base age A_b and an extra equivalent age ΔA , i.e.:*

$$\begin{aligned} A_m &= A_b + \Delta A \\ &= A_{\max} + \frac{2n_{\text{sub}}}{12} \\ &= A_{\max} + \frac{n_{\text{sub}}}{6} \quad [\text{yr}] \end{aligned} \quad (17)$$

where A_b is the maximum age A_{\max} gained by a testee who passes all six subtests required for a certain age, and ΔA is determined by the number of passed subtests beyond A_{\max} , i.e., n_{sub} .

Definition 17. *Intelligent quotient (IQ) is a ratio between the mental age A_m and the chronological (actual) age A_c , multiplied by 100, i.e.:*

$$\begin{aligned} IQ &= \frac{A_m}{A_c} \cdot 100 \\ &= \frac{A_{\max} + \frac{1}{6} n_{\text{sub}}}{A_c} \cdot 100 \end{aligned} \quad (18)$$

According to Definition 17, an IQ score above 100 indicates a certain extent of a gifted intelligence. However, the measure is sensitive only to children rather than adults, because the differences between the mental ages of adults cannot be formally defined and measured. Further, the basic assumption that the intelligent capability is linearly proportional along the growth of testee's age is inaccurate. Third, the norms or benchmarks of the mental ages for determining IQ are not easy to objectively obtain, especially for adults, and were considered highly subjective. More fundamentally, the IQ tests do not cover all forms of abstract intelligence as defined in GAIM, particularly the instructive and reflective intelligent capabilities.

The Turing Test

The second type of measurement for comparative intelligence is proposed by Alan Turing based on the Turing test (Turing, 1950) known as Turing intelligent equivalence.

Definition 18. *Turing intelligent equivalence E_T is a ratio of conformance or equivalence evaluated in a comparative test between of a system under test and an equivalent human-based system, where both systems are treated as a black box and the tester do not know which is the tested system, i.e.:*

$$E_T = \frac{T_c}{T_c + T_u} \cdot 100\% \quad (19)$$

where T_c is the number of conformable results between the two systems a tester evaluated, and T_u the number of unconformable results.

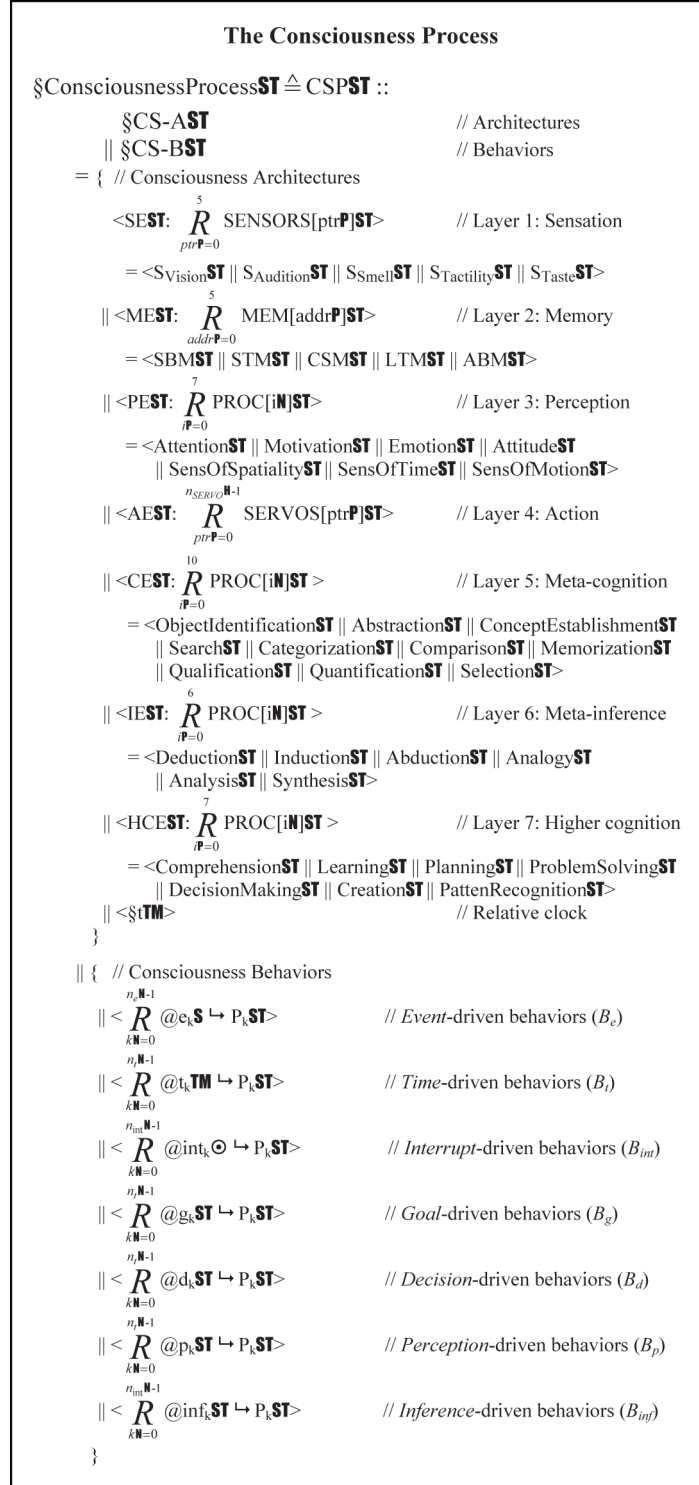
Turing tests with the layout above are informally defined based on empirical experiments and subjective judgement of conformance of testers, because the standard reference system of real human intelligent in the test is difficult to be defined and stabilized. Also, not all forms of intelligence as identified in GAIM may be tested by the black box setting such as the cognitive and reflective intelligent capabilities.

The Intelligent Metrics

Based on the understanding of the nature of abstract intelligence and the GAIM model (Wang, 2007d), a comprehensive measurement on human and system intelligence is proposed by the author known as the intelligent metrics as defined below.

Definition 19. *The Intelligent Capability \mathfrak{C}_i is an average capability of the perceptive intelligence (C_p), cognitive intelligence (C_c), instructive intelligence (C_i), and reflective intelligence (C_r), i.e.:*

Figure 3. The cognitive process of consciousness in RTPA



$$\mathfrak{C}_I = \frac{C_p + C_c + C_i + C_r}{4} \quad (20)$$

where $\mathfrak{C}_I \geq 0$ and $\mathfrak{C}_I = 0$ represents no intelligence.

In Definition 19, the four forms of intelligent capabilities can be measured individually according to the following methods given in Definitions 20 through 23.

Definition 20. The perceptive intelligent capability C_p is the ability to transfer a given number of data objects or events N_d into a number of information objects in term of derived or related concepts, N_i i.e.:

$$C_p = \frac{N_i}{N_d} \quad (21)$$

The perceptive intelligent capability is directly related to the association capability of a testee. The higher the ratio of C_p , the higher the capability of perceptive intelligence. If there is no concept that may be linked or derived for a given set of data or event, there is no perceptive intelligent capability.

Definition 21. The cognitive intelligent capability C_c is the ability to transfer a given number of information objects N_i in terms of associated concepts into a number of knowledge objects N_k in terms of relations between concepts, i.e.:

$$C_c = \frac{N_k}{N_i} \quad (22)$$

Definition 22. The instructive intelligent capability C_i is the ability to transfer a given number of information objects N_i in terms of associated concepts into a number of behavioral actions N_b in terms of number of processes at LRMB Layers 5 through 7, i.e.:

$$C_i = \frac{N_b}{N_i} \quad (23)$$

Definition 23. The reflective intelligent capability C_r is the ability to transfer a given number

of data objects or events N_d into a number of behavioral actions N_b in terms of number of processes at LRMB Layers 5 through 7, i.e.:

$$C_r = \frac{N_b}{N_d} \quad (24)$$

On the basis of Definitions 19 through 23, a benchmark of average intelligent capabilities can be established with a large set of test samples. Then, a particular testee's relative intelligent capability or intelligent merit may be derived based on the benchmark.

Definition 24. The relative intelligent capability $\Delta\mathfrak{C}_I$ is the difference between a testee's absolute intelligent capability \mathfrak{C}_I and a given intelligent capability benchmark $\overline{\mathfrak{C}_I}$, i.e.:

$$\begin{aligned} \Delta\mathfrak{C}_I &= \mathfrak{C}_I - \overline{\mathfrak{C}_I} \\ &= \frac{1}{4} \left(\frac{N_i}{N_d} + \frac{N_k}{N_i} + \frac{N_b}{N_i} + \frac{N_b}{N_d} \right) - \overline{\mathfrak{C}_I} \end{aligned} \quad (25)$$

The intelligent metrics provide a new approach to formally model and test abstract intelligence and their paradigms on the basis of GAIM. Adopting the intelligent metrics theory, natural and artificial intelligence may be quantitatively evaluated on the same foundation.

A UNIFIED FRAMEWORK OF ABSTRACT INTELLIGENCE AND ITS PARADIGMS

The preceding sections reveal the equivalence and compatibility between natural and artificial intelligence on the basis of abstract intelligence. Therefore, it is logical to state that natural intelligence should be fully understood before artificial intelligence can be rigorously studied on a scientific basis. It is also indicates that any machine which may implement a part of human behaviors and actions in information processing may be treated as the possession of some extent of intelligence.

The Architectural Framework of Abstract Intelligence

The architectural framework of abstract intelligence encompasses a wide range of coherent fields, as shown in Figure 4, from the computational, machinable, and artificial intelligence to natural intelligence in the horizontal scopes, and from the logical, functional, cognitive models to neural (biological) models in the vertical reductive hierarchy. Therefore, abstract intelligence forms the foundation of a multi-disciplinary and transdisciplinary enquiry of intelligence science.

Compatibility of the Intelligence Paradigms

According to the GAIM model, all paradigms of abstract intelligence share the same cognitive informatics foundation as described in the following theorems, because they are an artificial or machine implementation of the abstract intelligence.

Theorem 3. *The compatible intelligent capability state that natural intelligence (NI), artificial*

intelligence (AI), machinable intelligence (MI), and computational intelligence (CoI), are compatible by sharing the same mechanisms of αI , i.e.:

$$CoI \cong MI \cong AI \cong NI \cong \alpha I \quad (26)$$

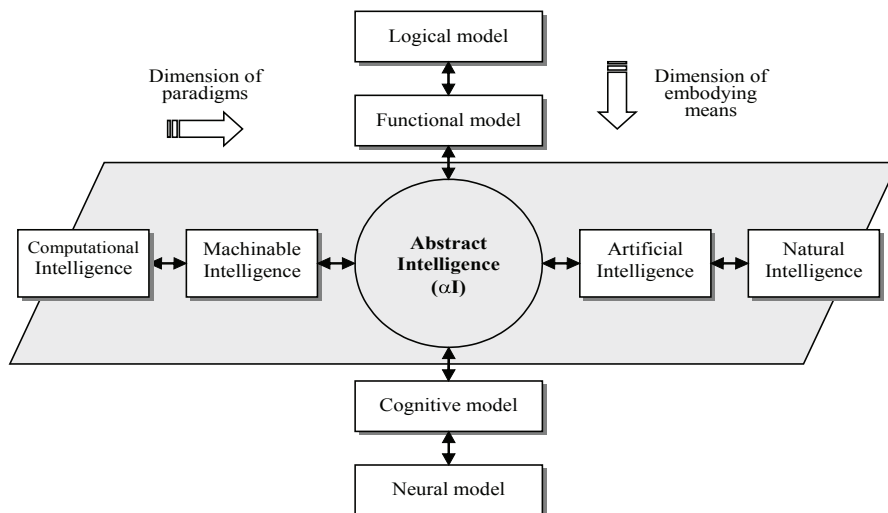
On the basis of Theorem 3, the differences between NI, AI, MI, and CoI are only distinguishable by: (a) The means of their implementation; and (b) The extent of their intelligent capability.

Corollary 3. *The inclusive intelligent capability states that all real-world paradigms of intelligence are a subset of αI , i.e.:*

$$CoI \subseteq MI \subseteq AI \subseteq NI \subseteq \alpha I \quad (27)$$

Corollary 3 indicates that AI, CoI, and MI are dominated by NI and αI . Therefore, one should not expect a computer or a software system to solve a problem where human cannot. In other words, no AI or computer systems may be designed and/or implemented for a given problem where there is no solution being known collectively by human beings as a whole. Further, Theorem 3 and Corollary 3 explain

Figure 4. The architectural framework of abstract intelligence and intelligence science



that the development and implementation of AI rely on the understanding of the mechanisms and laws of NI.

CONCLUSION

This article has presented a coherent theory for explaining the mechanisms of abstract intelligence and its paradigms such as natural, artificial, machinable, and computational intelligence. The taxonomy and nature of intelligence, and roles of information in the evolution of human intelligence have been explored. The Generic Abstract Intelligence Mode (GAIM) has been formally developed that provides a foundation toward the rigorous modeling of abstract intelligence. The intelligent metrics has been developed for measuring intelligent capability of humans and systems. Then, the compatibility of nature and machine intelligence has been established that unifies natural, artificial, machinable, and computational intelligence as real-world paradigms of abstract intelligence.

It has been recognized that abstract intelligence, in the narrow sense, is a human or a system ability that transfers information into behaviors; and in the broad sense, it is any human or system ability that autonomously transfers the forms of abstract information between data, information, knowledge, and behaviors in the brain. The abstract intelligence has been classified into four forms known as the perceptive, cognitive, instructive, and reflective intelligence. The logical model of the brain has been developed as the highest level of abstraction for explaining its cognitive mechanisms. Based on it, a systematical reduction from the levels of logical, functional, physiological, and biological has been enabled in order to form a coherent theory for abstract intelligence, brain science, and intelligence science.

ACKNOWLEDGMENT

The author would like to acknowledge the Natural Science and Engineering Council of

Canada (NSERC) for its partial support to this work.

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