# Web Intelligence Meets Brain Informatics

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**Abstract.** In this chapter, we outline a vision of Web Intelligence (WI) research from the viewpoint of Brain Informatics (BI), a new interdisciplinary field that systematically studies the mechanisms of human information processing from both the macro and micro viewpoints by combining experimental cognitive neuroscience with advanced information technology. BI studies human brain from the viewpoint of informatics (i.e., human brain is an information processing system) and uses informatics (i.e., WI centric information technology) to support brain science study. Advances in instrumentation, e.g., based on fMRI and information technologies offer more opportunities for research in both Web intelligence and brain sciences. Further understanding of human intelligence through brain sciences fosters innovative Web intelligence research and development. WI portal techniques provide a powerful new platform for brain sciences. The synergy between WI and BI advances our ways of analyzing and understanding of data, knowledge, intelligence, and wisdom, as well as their interrelationships, organizations, and creation processes. Web intelligence is becoming a central field that revolutionizes information technologies and artificial intelligence to achieve human-level Web intelligence.

## 1 Introduction

The term "Web Intelligence (WI)" was first introduced in 2000 [88]. As a new field of study, it presents excellent opportunities and challenges for the research and development of new generations of Web-based information processing technology, as well as for exploiting Web-based advanced applications [38,91,93]. In a previous paper [76], we discussed several perspectives of WI research:

> WI may be viewed as applying results from existing disciplines (e.g., Artificial Intelligence (AI) and Information Technology (IT)) to a totally new domain - the World Wide Web (the Web for short); WI may be considered as an enhancement or an extension of AI and IT; WI introduces new problems and challenges to the established disciplines.

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WI has been recognized gradually as a new research field on studying intelligence on the Web and intelligence for the Web.

Although WI related topics have been investigated separately in several existing disciplines, such as AI, Cognitive Science, and Neuroscience, there is a lack of a unified framework so that intelligence can be systematically studied for developing *human-level* Web intelligence. Brain Informatics (BI) is an emerging interdisciplinary field to systematically investigate human information processing mechanisms from both macro and micro points of view, by cooperatively using experimental, computational, cognitive neuroscience, and advanced WI centric information technology. It attempts to understand human intelligence in depth, towards a holistic view at a long-term, global vision to understand the principles and mechanisms of human information processing system (HIPS). The main objective of this chapter is to outline such a unified framework by examining what happens when *WI meets BI*. This leads to a new brain informatics perspective of WI research.

As more detailed blueprints and issues of WI are being evolved and specified [38,76,93,100], it becomes evident that one of the fundamental goals of WI research is to understand and develop wisdom Web based intelligent systems. Such systems integrate all human-level capabilities such as real-time response, robustness, autonomous interaction with their environment, communication in natural language, commonsense reasoning, planning, learning, discovery and creativity.

Turing gave the first scientific discussion of human-level machine intelligence [71]. Newell and Simon pioneered studies on programming computers for general intelligence [46]. McCarthy argued that reaching human-level AI requires programs that deal with the commonsense informative situation, in which the phenomena to be taken into account in achieving a goal are not fixed in advance [42]. Laird and Lent argued that interactive computer games are the killer application for human-level AI research, because they can provide the environments for research on the right kinds of problems that lead to the type of incremental and integrative research needed to achieve human-level AI [28].

In this chapter, we argue that human-level intelligence may be achieved by the combination of WI and BI. While the Web and the Web-based intelligent systems provide the necessary infrastructure for supporting BI research, as well as testbeds and applications of BI, BI research provides foundations to WI research. The rest of the paper is organized as follows. Section 2 details a new perspective of WI research. Section 3 examines how studies in two of the most fundamental WI related research areas, namely Autonomy Oriented Computing (AOC) and Granular Computing (GrC), interplay with those in BI. Section 4 describes several high-impact *WI meets BI* research topics. Finally, Section 5 gives concluding remarks.

## 2 A Brain Informatics Perspective of WI Research

There are urgent needs and great benefits of combining WI and BI research. Fundamental issues in both fields need to be investigated and integrated systematically in order to materialize those benefits.

### 2.1 What Is Brain Informatics?

Brain Informatics (BI) is an emerging interdisciplinary field to study human information processing mechanism systematically from both macro and micro points of view by cooperatively using experimental, computational, cognitive neuroscience and advanced WI centric information technology. It attempts to understand human intelligence in depth, towards a holistic view at a long-term, global vision to understand the principles and mechanisms of human information processing system (HIPS), with respect to functions from perception to thinking, such as multi-perception, attention, memory, language, computation, heuristic search, reasoning, planning, decision-making, problem-solving, learning, discovery and creativity. BI can be regarded as brain science in WI centric IT age [98,99]. BI is proposing to study human brain from the viewpoint of informatics (i.e., human brain is an information processing system) and use informatics (i.e., WI centric information technology) to support brain science study.

Figure 1 shows the relationship between BI and other brain science related disciplines as well as the WI centric IT. On one hand, although brain sciences have been studied from different disciplines such as cognitive science and neuroscience, BI represents a potentially revolutionary shift in the way that research is undertaken. It attempts to capture new forms of collaborative and interdisciplinary work. In this vision, new kinds of BI methods and global research communities will emerge, through infrastructure on the wisdom Web and knowledge grids that enables high speed and distributed, large-scale analysis and computations, and radically new ways of sharing data/knowledge. On the other hand, some of these lessons in cognitive science and neuroscience are applicable to novel technological developments in BI, yet others may need to be enhanced or transformed in order to manage and account for the complex and possibly more innovative practices of sharing data/knowledge that are made technically possible by the wisdom Web and knowledge grids [37,38,98].

### 2.2 Key Research Topics of Brain Informatics

In order to study BI systematically and give a global view to answer what is brain informatics, we list several major subtopics in each research area below, which is an extensional description of BI research.

- Thinking centric investigation of HIPS:
  - Human deductive/inductive reasoning mechanism for understanding the principle of human reasoning and problem solving;
  - Human learning mechanism for acquiring personalized student models in an interactive learning process dynamically and naturally.
- Perception centric investigation of HIPS:
  - Human multi-perception mechanism;
  - Auditory, visual and tactile information processing.
- Modeling human brain information processing mechanism:
  - Neuro-mechanism of HIPS;

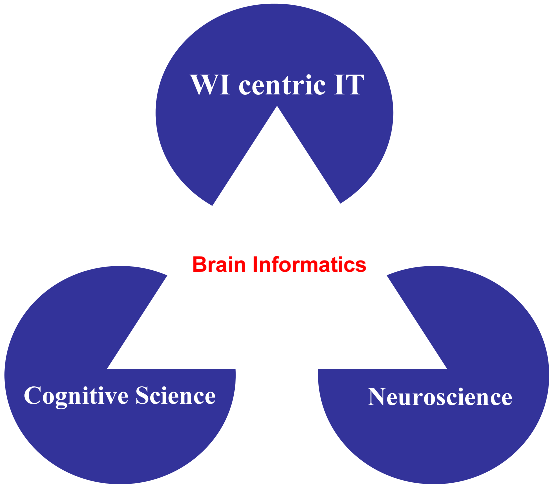


**Fig. 1.** The relationship between Brain Informatics and other brain science related disciplines as well as the WI centric IT

    - Mathematical models of HIPS;
    - Cognitive and computational models of HIPS.
- Information technologies for management and use of human brain data:
    - Human brain data collection, pre-processing, management, and analysis;
    - Multi-media human brain data mining and reasoning;
    - Databasing the brain and constructing data brain models;
    - Developing brain data grid and brain research support portals.

As a crucial step in understanding human intelligence, we must fully examine the mechanisms in which the human brain operates. The existing results, as reported over the last few decades about human information processing mechanism, are greatly related to progress of measurement and analysis technologies. Various non-invasive brain functional measurements are possible recently, such as fMRI and EEG. If these measurement data are analyzed systematically, the relationship between a state and an activity part will become clear. Furthermore, it is useful to discover more advanced human cognitive models based on such measurement and analysis. New instrumentation and new data analysis methods are causing a revolution in both AI and brain sciences [45,67].

In summary, BI emphasizes on a *systematic* approach for investigating human information processing mechanisms, including measuring, collecting, modeling, transforming, managing, mining, interpreting, and explaining multiple human brain data obtained from various cognitive experiments by using powerful equipments, such as fMRI and EEG. Human brain is regarded as an information processing system. A *systematic* study includes the investigation of human thinking centric mechanisms, the design of cognitive experiments, human brain data management, and human brain data analysis. Multi-aspect analysis in multiple human brain data sources based on a conceptual data model of human brain is an important methodology in BI.

### 2.3 "WI Meets BI" in Principle

As pointed out by McCarthy [42], if we understood enough about how the human intellect works, we could simulate it. However, so far we did not have sufficient ability to observe ourselves or others to understand directly how our intellects work. Understanding the human brain well enough to imitate its function requires experimental and theoretical success in cognitive science and neuroscience.

Neuroscience, the study of the brain and nervous system, is beginning to have direct measurement and observation of ourselves or others to understand directly how our intellects work. These measurements and observations are, in turn, challenging our understanding of the relation between mind and action, leading to new theoretical constructs and calling old ones into question. New instrumentation (fMRI etc.) and advanced information technologies are causing an impending revolution in WI and brain sciences. This revolution is bi-directional:

- **WI for BI:** WI based technologies (e.g., the wisdom Web, data mining, multi-agent, and data/knowledge grids) will provide a new powerful platform for brain sciences;
- **BI for WI:** New understanding and discovery of the human intelligence models in brain sciences (e.g., cognitive science, neuroscience, and brain informatics) will yield new WI research and development.

The first aspect means that WI technologies provide an agent based multi-database mining grid architecture on the wisdom Web for building a brain-informatics portal [95,98]. A conceptual model with three levels of workflows, corresponding to a grid with three layers, namely data-grid, mining-grid, and knowledge-grid, respectively, is utilized to manage, represent, integrate, analyze, and utilize the information coming from multiple, huge data and knowledge sources. Furthermore, wisdom Web based computing provides not only a medium for seamless information exchange and knowledge sharing but also a type of man-made resource for sustainable knowledge creation, and scientific and social evolution. The new generation Web will enable humans to gain practical *wisdoms* of living, working, and playing, in addition to information search and knowledge queries. The wisdom Web replies on multi-layer knowledge grids based service agencies that self-organize, learn, and evolve their courses of actions, in order to perform service tasks, as well as their identities and interrelationships in communities [37,38,91]. These service agencies cooperate and compete among themselves in order to optimize their own as well as others' resources and utilities. The proposed methodology attempts to change the perspective of cognitive/brain scientists from a single type of experimental data analysis towards a holistic view at a long-term, global field of vision.

The second aspect of the new perspective on WI means that the new generation of WI research and development needs to understand multi-nature of

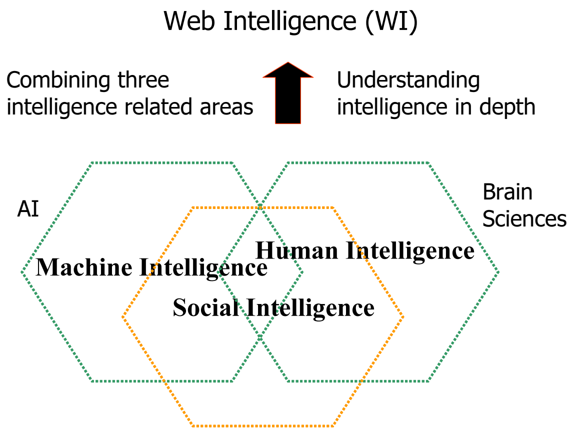


**Fig. 2.** The relationship between WI and other three intelligence related research areas

intelligence in depth, by studying together the three intelligence related research areas: machine intelligence, human intelligence, and social intelligence, as illustrated in Fig. 2, towards discovery of new cognitive and computational models for developing truly human-level Web intelligence.

Machine intelligence (or Artificial Intelligence) has been mainly studied as computer based technologies. Various computational models and knowledge based systems have been developed for automated reasoning and learning. Unfortunately, most of such models and systems will not work well when dealing with large-scale, global, distributed, multiple information sources on the Web. BI presents new opportunities as well as challenges to solve the difficulty, that is, to find a good way of bridging the huge gap between classical automated reasoning/learning and biologically plausible reasoning/learning.

On the other hand, human intelligence is concerned with the nature of intelligence towards our understanding of intelligence. The capabilities of human intelligence can be broadly divided into two main aspects: perception and thinking. So far, the main disciplines with respect to human intelligence are cognitive science that mainly focuses on studying mind and behavior based cognitive models of intelligence, as well as neuroscience that mainly focuses on studying brain and biological models of intelligence. In cognitive neuroscience, although many advanced results with respect to "perception oriented" study have been obtained, only a few of preliminary, separated studies with respect to "thinking oriented" and/or a more whole information process have been reported [17]. Study of HIPS from the *WI meets BI* point of view should be "thinking oriented".

Furthermore, social intelligence needs a combination of machine intelligence and human intelligence for establishing social networks that contain communities of people, organizations, or other social entities [91]. One of the important implications of the Web is that it introduces a social network where a set of people (or organizations or other social entities) are connected. The connections are based on a set of social relationships, such as friendship, co-working or information exchange with common interests. In other words, it is a Web-supported social network or virtual community. In this sense, the study of WI is of social network intelligence (social intelligence for short).

Figure 3 shows the relationship between WI and BI research. The synergy between WI with BI will yield profound advances in our analyzing and understanding of the mechanism of data, knowledge, intelligence and wisdom, as well as their relationship, organization and creation process. It means that WI fundamentals and technologies will be studied as a central topic and in a unique way. It will change the nature of information technologies in general and artificial intelligence in particular, working towards a new understanding and development of human-level Web intelligence.

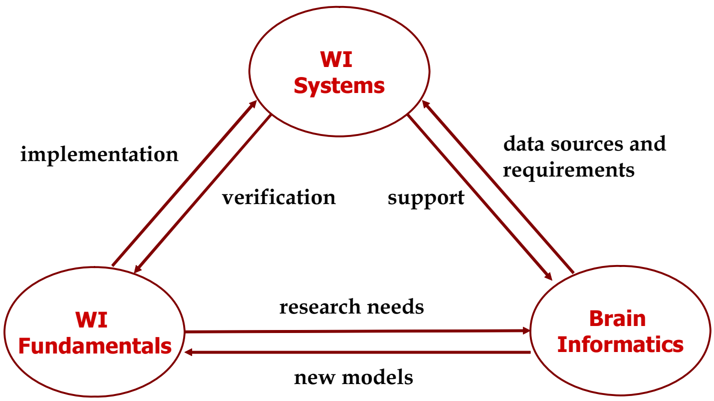


**Fig. 3.** The relationship between WI and BI research

## 3 "WI Meets BI" in Fundamental Research

Making a detailed plan for *WI meets BI* research (including the detailed systematic fMRI/EEG experiment plan) is one of the most urgent tasks. Unfortunately, there is a gap between WI and brain science research. Finding a better way to bridge this gap is the key to success in *WI meets BI*. Figure 4 provides a schematic diagram that depicts three facets of WI related research and development, i.e., fundamentals, technologies, and applications. In what follows, we will take an in-depth look at the fundamental facet, and in particular, describe how studies in two of the most fundamental WI related research areas, namely Autonomy Oriented Computing (AOC) and Granular Computing (GrC), will interplay with those in BI, hence narrowing such a gap.

### 3.1 The AOC Dimension

**Autonomy Oriented Computing (AOC): What and How?** The goals of AOC [40,34] are: (1) to discover and understand the working mechanisms that

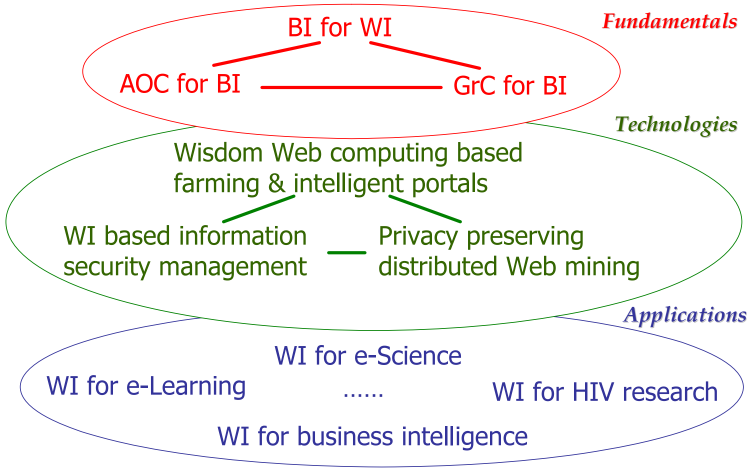


**Fig. 4.** Three facets of WI related research and development

lead to emergent behavior in complex systems (e.g., the dynamics of WWW, social networks, and immune systems), and (2) to design and develop scalable solutions to large-scale, distributed computational problems (e.g., distributed optimization in sensor network data routing, robot world modeling, and dynamic grid resource allocation).

In doing so, AOC emphasizes the modeling and characterization of *autonomous* entities in the systems or problems at hand, and thereafter, creates a computational system that enables the modeled entities to locally interact following certain nature or real-world inspired rules. An AOC system is an open, non-equilibrium system in which autonomous entities are free to react to external stimuli and to actively carry out information exchanges or utility updates based on the predefined behavioral rules. As a result, certain behavior of the entities and/or their effects will be nonlinearly aggregated and amplified as opposed to others. This process is known as *self-organization*, which can be regarded as the *core* of AOC.

**The Distinct Characteristics of AOC.** In complex systems modeling, AOC enables the process of self-organization to effectively recap certain empirically observed emergent behavior and hence provide a model for its working mechanism [36]. In complex problem solving, AOC utilizes self-organization to efficiently converge to a *desired* solution state [35,33]. The benefits of AOC in either case can be summarized as follows:

1. AOC lends itself very well for *natural formulation*, since many complex systems or problems at hand are locally-interacting, autonomous, and distributed in nature;
2. AOC provides an *easy-to-implement* computing or programming means, as autonomous entities can readily be developed and deployed;

3. AOC offers *scalable performances* in both systems modeling and problem solving, as the spirit of self-organization lies in the fact that the larger the scale, the more effective and efficient the process should become.

From the above-mentioned characteristics and/or benefits, we can note that AOC differs from conventional agent-based computing, as the latter is aimed primarily at providing a distributed software or system development methodology that is based on the models of rational agents. At the same time, it also differs from conventional agent-based simulation, as the goals of AOC are made both more explicit and broader.

**The Basic Elements of AOC.** As may be noted from the above, there are several basic elements essential to an AOC system, some of which are outlined below.

1. **Environment:** As one of the main components in an AOC system, the environment serves not only as the domain for autonomous entities, but also as an indirect communication medium among entities.
2. **Autonomous Entities:** An autonomous entity reacts to other entities as well as the environment. It modifies its exert changes to the environment, and/or affect other entities. Central to an autonomous entity is its *local behavior* and *behavioral rules* that govern how it should act or react to the information
3. **Interactions:** The emergent behavior of an AOC system originates from its internal interactions. Generally speaking, there are two types of interactions, namely, *interactions between entities and their environment* and *interactions among entities*. Different AOC systems may have different ways of direct or indirect interactions among their entities. Indirect interactions are implemented through the communication medium role of the environment.

For further readings on AOC, e.g., comprehensive surveys of related work, formal descriptions of the AOC approaches and formulations, and detailed discussions of examples, please refer to [40].

**AOC for BI.** Human brain is one of the most complex systems that we have ever encountered. Central to human consciousness, cognition, and emotion is the emergence of mental complex behavior based on the self-organization of neurons and neural activities; some of the emergent patterns with respect to certain specific conditions or tasks can be experimentally measured and visualized using brain imaging technologies.

Many interesting observations have been made regarding the complex nature of how we think, and can be found in [55].

The goals of BI are twofold: (1) to measure, characterize, and predict how humans think and reason, and in turn (2) to provide new insights into how to develop and build real-world, large-scale AI systems, e.g., in the context of WI. Both goals complement well with those of AOC as mentioned above. This can be viewed in the following two important aspects.

**AOC Informs BI.** AOC provides an ideal means for the advancement of BI. AOC can be used to hypothesize and model the underlying interactions and tempospatial interrelationships among different regions and/or functions in the human brain with respect to performing various cognitive tasks, such as learning, reasoning, and decision making. In other words, AOC can *inform* neuroscience and BI studies as to what areas, interactions, information exchange mechanisms, and/or cognitive strategies to look into, following the AOC's *white-box* modeling results.

For instance, based on the AOC-based approach to regularity characterization [36], it is now possible to explicitly model WWW users, including their interest profiles, motivations, and navigation strategies or decision-making processes, and to study how those attributes lead to different emergent regularities on the WWW. The approach views users as *information foraging entities* categorized into three different categories: *recurrent*, *rational*, and *random users*. Users of different categories will apply different sets of navigation behavior. The AOC-based results match well with the known empirical results; in other words, they offer a white-box model of user navigation behavior that can be used to explain the self-organized WWW regularities. As a natural extension, we may further validate the modeled user navigation behavior through BI studies, so as to confirm the AOC findings.

**BI Guides AOC.** Findings from BI studies can, on the other hand, provide a guidance to the design and formulation of new AOC models and methods, e.g., for identifying the behavioral rules of underlying autonomous entities/ components and their self-organizing processes [51].

For instance, one of the interesting AOC studies in the context of WI is to develop autonomous search and reasoning mechanisms, whose performance can scale well in light of large-scale, distributed, and heterogeneous content resources, as in the case of WWW. As mentioned above, the core of the AOC-based approach is to create a non-linear process of self-organization that can make the search or reasoning 'behavior' not only possible but also *scalable*. In this regard, a better understanding of human cue-based association, extraction and abstraction behavior would be helpful in either developing new AOC-based search and reasoning mechanisms or building a basis for further AOC-based characterization.

**How Are Things Connected?** *Nature* has unfolded many interesting regularities and properties, some of which are quite ubiquitous [26]. A well-observed example is self-organized criticality, as described in Bak's *How Nature Works* [4]. At the same time, there also exist other things in nature, about which we are so fascinated but still know very little. The most obvious example is our *brain*; references on some of the existing findings and hypotheses can be found in Pinker's *How the Mind Works* [55].

As a nature inspired computing paradigm, autonomy oriented computing *naturally* brings the two together. On one hand, AOC explicitly draws on and utilizes the metaphors of autonomy as offered by nature and the natural law of self-organization as the advocated computational means for complex systems modeling and problem solving. On the other hand, as mentioned in the preceding subsections, AOC can readily play an important role in unveiling and explaining human brain's mental regularities.

### 3.2 The GrC Dimension

Granular computing (GrC) is a multi-disciplinary study of human-centered and knowledge-intensive problem solving at multiple levels of granularity [5,6,25,32,48,53,54,56,57,63,75,89]. A unified framework of granular computing can be established by focusing on the philosophical, methodological and computational perspectives [77,81,82]. This framework may provide insights into our understanding of the working mechanism of human information processing and would eventually lead to an abstract and conceptual model of the brain.

**Overview of Granular Computing.** Granular computing deals with problem solving in terms of the parts and the whole. Parts may be viewed as granules situated in the context of a whole. Furthermore, a part can also be a whole consisting of smaller parts. Thus, granular computing focuses on multiple hierarchical structures of granules [5,10,77,81,82,86].

Hierarchical organizations and structures are abundant in the real world. They can be found in many natural, social, and man-made systems [1,2,52,62,64]. Human perception and understanding of the real world depends, to a large extent, on such nested and hierarchical structures. We perceive and represent the world using various grain sizes, and abstract only those things that serve our present interests [23,41,62,83,84]. The ability to conceptualize the world at different granularities and to switch among these granularities is fundamental to human intelligence and flexibility [23].

Granular computing explores the hierarchical structures for an understanding of human intelligence in problem solving and apply it for the design and implementation of intelligent information processing systems. Granular computing may be studied based on the following three interrelated perspectives [81]:

- Philosophical perspective: structured thinking;
- Methodological perspective: structured problem solving;
- Computational perspective: structured information processing.

The multiple levels structures, mathematically defined by a partial ordering, are the central notion that links the three perspectives. In a nutshell, granular computing studies ways of thinking, information processing and computing using structures.

**Importance of a Conceptual Model of the Brain.** It is a common practice to compare the a human and a computer in order to gain an understanding of the one with the aid of the other. For example, one may draw many correspondences between them, including CPU to the brain, input/output devices to human perceptive organs, and memory to memory. At even lower levels, logic gates are compared to neurons and wires are compared to neuron connections. While such an understanding is sufficient for certain purposes, it may be inadequate for the understanding of natural intelligence emerged from the human brain.

A conceptual brain model is perhaps still a less studied and understood problem in brain informatics research. In this respect, the von Neumann architecture of computers may shed some light. We can easily convince ourselves that the von Neumann architecture is the foundation of modern day computer. If a different conceptual model was used, we would have a much different type of computers today. Furthermore, without the von Neumann architecture, it will be much more difficult to obtain an understanding of a computer. On the one hand, we may have equipment that allows us to measure physical properties and to observe the behavior of a computer. On the other hand, an understanding of a computer cannot easily be obtained from such measurements and observations. We need conceptual models, like the von Neumann architecture, to put all puzzle pieces together.

The study of human brain is in a similar situation. On the one hand, we have achieved extensive results in neural science and cognitive science. We have detailed description and in-depth understanding of the brain at the neuron level and the cortex region level. The new instruments, such as fMRI, make the observation of the brain more accurate and detailed. On the other hand, there is still a lack of a commonly agreed conceptual model that enables us to see the high level working principles of the brain.

Some researchers have in fact made very promising progress towards conceptual models of the brain. For example, Hawkins uses the notion of a cortical hierarchy for deriving a memory-prediction framework for explaining intelligence [22]. A conceptual model of cortex is proposed by highlighting its hierarchical connectivity and information flow up and down the hierarchy [22]. To some extent, this conceptual model is closed related to the study of granular computing [82].

An urgent task of brain informatics research is therefore to build a conceptual framework of the brain. As a minimum requirement, this framework must cover information processing in the abstract, in the brain, and in the machine. By studying information processing in the abstract, we may be able to build conceptual models that explain how the brain works; the understanding of the brain and its information processing mechanism will provide new insights into how to implement intelligence and information processing in machines.

**The Relevance of Granular Computing.** The basic principles of granular computing, namely understanding and working with multiple levels of granularity, may capture the essential features of human problem solving and human intelligence. Based on such principles, one may study brain informatics from multiple views and at multiple levels in each view.

*The power of evolution.* The human brain may be viewed as a natural system in the long history of evolution. Some of the functions of the brain are to perceive, analyze, synthesize, store and retrieve information about its environments, as well as using such information in decision making. As a result, it is reasonable to assume that the brain is good at processing structures and patterns that are abundant in nature. Furthermore, the brain is able to deal with structures at differing levels of granularity.

A very common and dominant structure is a hierarchical structure, mathematically defined by a partial order. The levels in the structure show the differing degrees of abstraction, control, orderness, structuredness, details, and so on. The brain has amazingly capacity to deal with such structures. Some researchers have suggested hierarchical modeling of the brain. The cortex hierarchical organization is perhaps generally accepted for human vision [41]. Hawkins argues that this view may be more generally applicable [22]. According to him, the human brain can be interpreted as a hierarchical structure that stores a model of the hierarchical structure of the real world. In other words, the real world's nested structure is mirrored by the nested structure of our cortex.

As an emerging multi-disciplinary study, granular computing deals with hierarchical structures with multiple levels of granularity. This makes it very relevant to the study of brain informatics. If we believe in the power of evolution, we need to accept that the working principles of the brain can be related to the working principles of the real world. This is the foundation of our search for a conceptual model of the brain based on the ideas of granular computing.

*Roles of languages in information processing and natural intelligence.* Concepts are the basic unit of human thoughts and play a central role in our understanding of the world. Languages, either special purpose languages such as logic, mathematics, and programming languages or general purpose natural languages, are developed as ways to represent our thoughts and to communicate with each other. Human information processing and natural intelligence depend crucially on our language ability.

Hierarchical structures of a language can be observed from two aspects. In one aspect, a language itself consist of a set of components that can be arranged hierarchically. For example, in English we have letters, words, phrases, sentences, paragraphs, and articles. They are nested within each other to form a hierarchy. In the other aspect, we can easily observe the hierarchical structure of things described by a language. Similar to Hawkins' argument, the hierarchical structures of a language is determined by the things it is intended to describe. That is, the structures of language again mirror the structures of the real world.

It seems reasonable to start from an assumption that human brain processes information by exploring the hierarchical structures. For example, when reading an article, our eyes may see a text a sequence of letters at a lower level, our short term memory may view it as a sequence of words or sentences at a higher level, and our long term memory may view it as a set of ideas at an even higher level. Such a sequence of abstraction may provide clues on human information processing and intelligence. Human vision may be similarly interpreted, if we view pictures and images as things described by a different type of language.

*Data, Information, Knowledge and Wisdom hierarchy.* From the practical side, results from the study of granular computing for brain informatics may be applied to design and implement better Web-based intelligent information systems.

In computer science, we have studied many approaches for representing and processing information and knowledge. Typically, knowledge representation methods must deal with the issues of granularity. Data, information, knowledge, and wisdom may be viewed as the descriptions of the same world at different levels of granularity. Since we have the same underlying world, it is possible to transform data into information, information into knowledge, and knowledge into wisdom. The brain has the ability to process and work with all those types. While data is more related to our perceived sensory level ingredients, others are related to synthesized results.

The data, information, knowledge, and wisdom hierarchy also captures the evolution of the World Wide Web, change from data Web, to information Web, to knowledge Web, and to wisdom Web [38,80,91]. With a deeper understanding of information processing in the abstract, in the brain and in machine, we may be moving closer to the wisdom Web [38,91].

There is evidence supporting our views presented here. However, we are still far away from a real framework. The main objective is to stimulate discussion and further research. Although the details may be refined or change with more understanding of the problem, research on such a conceptual model is perhaps on the right track.

## 4 Impending *"WI meets BI"* Research

We briefly report our high-impact research projects to demonstrate the potentials of combining WI and BI.

### 4.1 Reasoning Centric, Thinking Oriented Studies of HIPS

Figure 5 presents a schematic diagram of reasoning centric, thinking oriented functions and their relationships. It represents an attempt for a systematic examination of human thinking centric mechanisms. The core issue is to investigate human deduction, induction, and abduction related reasoning mechanism, including commonsense and non-monotonic reasoning, as shown in the central of Figure 5. Heuristic search, autonomy (related to AOC), information granulation (related to GrC), attention and memory are some component functions to implement human reasoning, as well as emotion, uncertainty and stability are some interesting characteristics, which should be investigated with respect to human reasoning, as illustrated in the middle circle of this figure. Furthermore, decision-making, problem-solving, planning, computation, language, learning, discovery and creativity are the major human thinking related functions, which will be studied systematically, as illustrated outside the middle circle of this figure.

Research in cognitive neuroscience, including brain lesion and brain imaging studies of normal subjects, have made some preliminary progresses for the brain mechanism of deductive/inductive reasoning. Patients studies can provide some rough localization result of inductive reasoning. For example, Gazzaniga and colleagues administered simple inductive reasoning tasks to split-brain patients

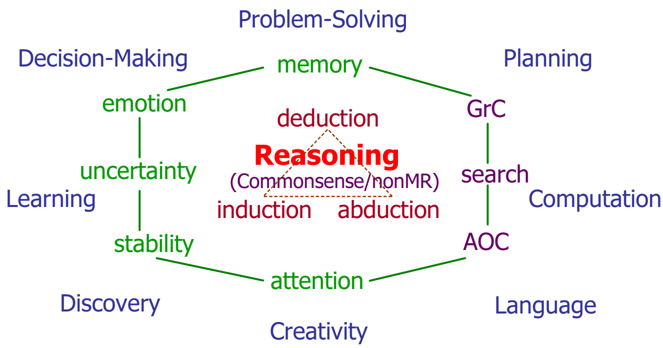


**Fig. 5.** A systematic illustration of reasoning centric, thinking oriented functions and their relationships (GrC: Granular Computing [78]; AOC: Autonomy Oriented Computing [40]; nonMR: non-monotonic reasoning)

and concluded that reasoning is a left hemisphere phenomenon [15]. Furthermore, Gazzaniga postulated a "left brain interpreter" [16]. Varley and colleagues suggested that induction may recruit dorsolateral and medial aspects of the prefrontal cortex [72]. However, the results of patients may be insufficient to tell us more details about the spatiotemporal characteristics of inductive reasoning. Nowadays, brain imaging of normal subjects is the most popular way for researchers. Goel and colleagues used PET to examine human deductive/inductive reasoning when subjects performed sentential inductive tasks for the first time [18]. With the new event-related fMRI technique, Goel and colleagues performed similar experiments, and indicated that left dorsolateral prefrontal gyrus showed a greater activity during induction than deduction [20]. Christoff and colleagues hypothesized that the process of relational integration is a component process of inductive reasoning [11]. Some adapted RPM (Raven's Progressive Matrices) tasks were used in their experiment, and the results indicated that the process of relational integration is specifically associated with the bilateral rostrolateral PFC (RLPFC, BA 10) and the right dorsolateral PFC (DLPFC, BA 9 and 46). Goel and colleagues adopted novel animals as induction stimuli, and the fMRI results showed that rule inference was specifically associated with the bilateral hippocampal activation while the task characterized by difficulty interaction was associated with activation in the right lateral orbital prefrontal cortex [19].

However, there are limited experimental studies in cognitive neuroscience. In particular, the aforementioned brain imaging studies mainly have two flaws. Firstly, for sentential tasks and RPM tasks, individual difference induced by background knowledge of tasks is significant, i.e., the effects of background knowledge cannot be well counterbalanced. Secondly, all these studies mainly employed PET or fMRI technique to explore the functional dissociation among activated brain regions. Due to their low temporal resolution, we still know little about the time course of inductive reasoning process in human brain.

Our purpose is to understand activities of HIPS by investigations in the following two levels:

- investigating the spatiotemporal features and flow of HIPS, based on functional relationships between activated areas of human brain for each given task;
- investigating neural structures and neurobiological processes related to the activated areas [61].

More specifically, at the current stage, we want to understand:

- How a particular part (one or more areas) of the brain operates at a specific point of time;
- How the operations change over time;
- How the activated areas are linked, indexed, and navigated functionally?
- How the activated areas work cooperatively to implement a whole information processing functionality;
- How a cognitive process is supported by neurobiological processes;
- What are individual differences in performance.

The key question is "can we find a new cognitive model for developing human-level Web based network reasoning and problem solving?".

**Human and Web Problem Solving and Reasoning.** As an example of thinking oriented studies for WI meets BI, we describe a study of human and Web problem solving and reasoning in a unified way. The objective is to develop Web based problem solving system with human-level capabilities.

Problem-solving is one of main capabilities of human intelligence and has been studied in both cognitive science and AI, where it is addressed in conjunction with reasoning centric cognitive functions such as attention, control, heuristic search, reasoning, learning, and so on, using a logic based symbolic and/or connectionist approach. Logic based problem-solving may be viewed as theoretic models that are mathematical systems with no real time and memory constraints. Web-based problem-solving systems need real-time response and deal with global, multiple, huge, distributed information sources.

A more concrete issue of WI is the development and application of a Web-based problem-solving system for portal-centralized, adaptable Web services [38,69,91,93]. The core of such a system rests on the Problem Solver Markup Language (PSML) and PSML-based distributed Web inference engines for network reasoning. PSML should support at least the following essential functions:

- Supporting complex adaptive, distributed problem solving;
- Performing automatic reasoning on the Web by incorporating globally distributed contents and meta-knowledge, automatically collected and transformed from the semantic Web and social networks, with locally operational knowledge-data bases;
- Representing and organizing multiple, large-scale knowledge-data sources for distributed network reasoning;

- Combining multiple reasoning methods in PSML representation and distributed inference engines efficiently and effectively;
- Modeling user behavior and representing/managing it as a personalized model dynamically;
- Developing the Web based reasoning and problem solving system, with a consideration of an emotional factor.

As a first step, a possible way for implementing certain distributed reasoning capabilities of the future PSML is to make use of an existing logic language coupled with agent technologies. We have demonstrated one possible implementation of such capabilities. A preliminary version of an implementation, called $\beta$-PSML, is based on the combination of OWL with Horn clauses and is able to couple global semantic Web/social networks with local information sources for solving problems in a large-scale distributed Web environment [68,69].

In order to develop a Web based problem-solving system with human-level capabilities, we need to better understand how human being does complex adaptive, distributed problem solving and reasoning, as well as how intelligence evolves for individuals and societies, over time and place [67,85,99]. Ignoring what goes on in human brain and focusing instead on behavior has been a large impediment to understand complex human adaptive, distributed problem solving and reasoning.

In the light of BI, we need to investigate specifically the following issues:

- What are the existing thinking/reasoning models in AI, cognitive science, and neuroscience?
- How to design fMRI/EEG experiments and analyze such fMRI/EEG data to understand the principles of human reasoning and problem solving in depth?
- How to build the cognitive model to understand and predict user profile and behavior?
- How to implement human-level reasoning and problem solving on the Web based portals that can serve users wisely?

As a result, the relationships between classical problem solving and reasoning and biologically plausible problem solving and reasoning need to be defined and/or elaborated.

In summary, human and Web problem solving and reasoning needs to be studied in a unified way, based on the following approach: (1) to investigate the mechanisms of human problem solving and reasoning from a BI perspective; (2) to investigate AOC based problem solving and reasoning; (3) to investigate GrC based problem solving and reasoning; (4) to develop and validate new cognitive/computational models for Web-based problem solving and reasoning, based on the results from the studies of (1)-(3).

**Studying Lower and Higher Functions of HIPS.** Functions of HIPS can be classified as the lower and higher functions. This classification is not a mechanistic one, but relative and from a global view. Thinking oriented study in HIPS needs to understand relationship between lower and higher functions of HIPS.

If we want to understand the mechanism of higher functions, such as reasoning, problem-solving and decision-making, we need to understand the mechanism of lower functions, such as attention, memory, vision, and their relationship. We give some research examples in order to explain the relationship between lower and higher functions, from the viewpoint of a perception oriented study.

1. **Visual, Auditory and Calculated Functions.** Human visual and auditory systems have been evolving through the long history and have attained very high performance. However, artificial systems for those are often poorer in performance despite of remarkable progress in their efficiency. In order to construct artificial systems with high performance, such as human visual and auditory systems, it is necessary to elucidate the mechanisms of human visual and auditory systems. In order to investigate the characteristics of human visual and auditory information processing, the authors have measured the function of human brain related to calculation. For the tasks of measuring the human information processing involving calculation, the characteristics of the visual and auditory information processing were measured by using the mental arithmetic problems as the visual and auditory stimuli by psychological experiment. Activated areas of human brain related to the calculation were also measured by fMRI. The measurement results clearly show the difference between the visual and auditory calculation. They provide evidence for explaining the mechanism of visual and auditory information processing and may have an impact on the construction of artificial systems [29,44].
2. **Auditory and Language Functions.** Function segregation in the left inferior frontal gyrus was investigated in an fMRI experiment using a passive listening task, in which Japanese subjects were required to passively listen to words and non-words in Japanese and English. Listening to English words and non-words activated the bilateral dorsal inferior frontal gyrus more extensively than listening to Japanese words and non-words, implying an automatic articulatory representation access for harder perception effort of the nonnative language stimuli. In both languages, word listening activated the left ventral inferior frontal gyrus more extensively than nonsense word listening, suggesting a lexical or semantic processing function. This function segregation in the left inferior frontal gyrus has also been found in studies using visual tasks [8,74].

On the other hand, from the viewpoint of thinking oriented study, we need to consider what are the relationship and difference between the perception and thinking oriented studies. Based on BI methodology, we can develop an approach to unify the perception and thinking oriented studies in some cognitive level. In other words, by a systematic design of cognitive experiments in BI methodology, the data obtained from a cognitive experiment and/or a set of cognitive experiments may be used for multi-task/purpose, including for both lower and higher functions. For example, it is possible that the experiment for investigating visual, auditory and calculated functions as mentioned above is re-designed to meet requirements of both thinking and perception oriented studies for multi-task/purpose (e.g. investigating the mechanisms of human visual and auditory systems, computation, problem-solving, and the spatiotemporal feature and flow of HIPS).

**Cognitve Architecture Meets fMRI/EEG.** According to Newell [47], cognitive architecture would explain how all the components of the mind work together to generate coherent human cognition [3]. Therefore, it is also a kind of effort towards conceptual modeling of the brain. ACT-R, one of the best known, fully implemented, and free to public cognitive architecture models, is a theory on how the structure of brain achieves the function of adaptive cognition in a system level, as well as a platform to build computational models to simulate/predict human cognitive behavior, including performing complex dynamic tasks, which usually emphasize perceptual-motor components and their coordination with other cognitive components (learning and memory, reasoning, and so on) and with strong time pressure [3,65], as usually required by Web tasks.

Consistent with granular computing, ACT-R has two levels. The subsymbolic level deals with fine-graded models of learning and performance. In the symbolic level, ACT-R consists of modules. Consistent with Autonomy Oriented Computing, the processes of the interaction between the inside modules and the outside world as well as the interaction among these modules. The output of an ACT-R model is a time course for when and how long the activations of each module involved in the task are. Based on it, one can predict the performance of the subjects (such as reaction time and accuracy). Recent years, the modules in ACT-R have been mapped to brain areas, and methods have been developed to predict Blood Oxygenation Level-Depend (BOLD) effect in fMRI experiments, as shown in the chapter of ACT-R meets fMRI.

Technologies have been developed to check the synchronous neural oscillations from EEG data, which may reveal the dynamic cognitive processes in brain [73]. Thus EEG and ACT-R (with fMRI) will provide two aspects to infer the cognitive processes and their neural basis. Therefore, combining cognitive architecture, fMRI and EEG might be an appropriate approach to help us to reach the goal described in this section, investigating the spatiotemporal feature and flow of HIPS and investigating neural structures and neurobiological processes related to the activated areas. In addition to the tasks mentioned in other sub-sections, we need to systematically perform a set of behavior, fMRI and EEG experiments, and with the help of ACT-R modeling, to explore the cognitive processes and their neural bases of human interacting with the Web and to have a better understanding of WI and BI.

### 4.2 Studying the Full Process from fMRI/EEG Experiments to New Cognitive WI Models

Figure 6 shows a full process from designing fMRI/EEG experiments based on WI needs to discovering new cognitive WI models. It offers a systematic approach for measuring, collecting, modeling, transforming, managing, and mining multiple human brain data obtained from various cognitive experiments by using fMRI and EEG [96,98].

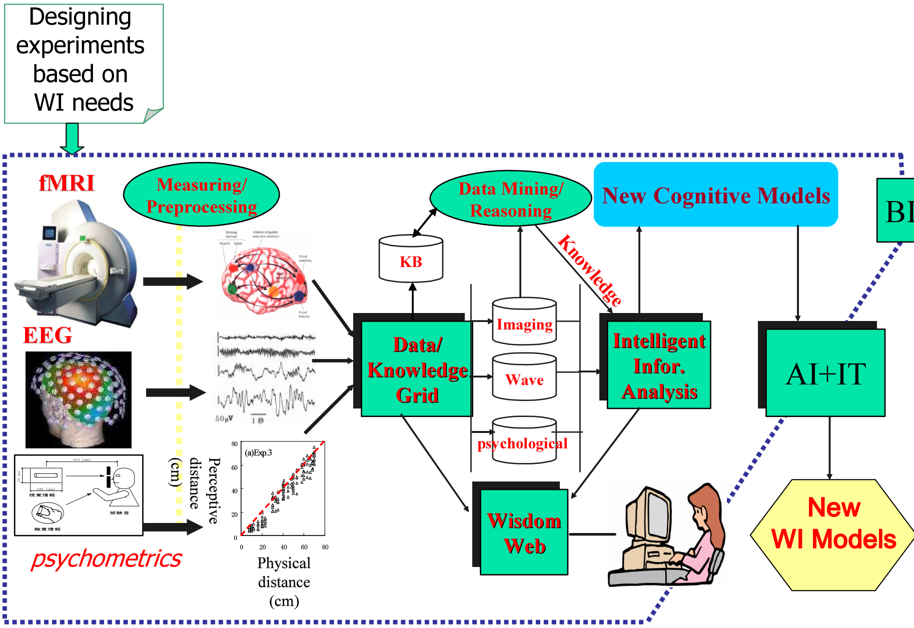


**Fig. 6.** From fMRI/EEG experiments to new cognitive WI models

Each of fMRI and EEG technologies has its strength and weakness from the aspects of time and space resolutions. fMRI provides images of functional brain activity to observe dynamic activity patterns within different parts of the brain for a given task. It is excellent in the space resolution, but inferior in the time resolution. On the other hand, EEG provides information about the electrical fluctuations between neurons that also characterize brain activity, and measurements of brain activity at resolutions approaching real time. In order to discover new knowledge and models of human information processing activities, not only individual data source obtained from a single measuring method, but also multiple data sources from various practical measuring methods are required.

The future of BI will be affected by the ability to do large-scale mining of fMRI and EEG brain activation data. The key issues are how to design the psychological and physiological experiments for systematic obtaining various data from HIPS, as well as how to analyze and manage such data from multiple aspects for discovering new models of HIPS. Although several human-expert centric tools such as SPM (MEDx) have been developed for cleaning, normalizing and visualizing the fMRI images, researchers have also been studying how the fMRI images can be automatically analyzed and understood by using data mining and statistical learning techniques [43,45,66,70,96]. We are concerned with how to extract significant features from multiple brain data measured by using fMRI and EEG in preparation for multi-aspect data mining that uses various data mining techniques for analyzing multiple data sources.

**Building a Brain-informatics Portal.** Building a brain-informatics portal is, in fact, to develop a data mining grid centric multi-layer grid system on the wisdom Web for multi-aspect data analysis. The wisdom Web [37,38] and Grid computing [9,14] have provided the ideal infrastructures, platforms, and technologies for building such a brain-informatics portal to support cognitive/brain scientists in multi-aspect analysis in multiple, large-scale data sources. We need to study experimental cognitive neuroscience, data mining, intelligent agents, data and knowledge grids, the semantic Web and wisdom Web in a unified way.

*Middleware*, as a new platform, is required to cope with multiple huge, distributed data sources for multi-aspect analysis in building a brain-informatics portal on the wisdom Web. It is necessary to create a grid-based, organized society of data mining agents, called a *data mining grid* on the Grid computing platform (e.g. the Globus toolkit) [14]. This means:

- developing various data mining agents for various services oriented multi-aspect data analysis;
- organizing the data mining agents into a Grid with multiple layers such as data-grid, mining-grid, and knowledge-grid, under the OGSA (Open Grid Services Architecture) that firmly aligns with service-oriented architecture and Web services, in order to understand the user's questions, transform them to data mining issues, discover the resources and information about the issues, and get a composite answer or solution;
- using a conceptual model with three levels of workflows, namely data-flow, mining-flow, and knowledge-flow, corresponding to the three-layer Grid, respectively, for managing data mining agents for multi-aspect analysis in distributed, multiple data sources and for organizing the dynamic, status-based processes of brain informatics study.

The data mining grid is made of many smaller components that are called *data mining agents*. Each agent by itself can only do some simple thing. Yet when joining these agents on the Grid, more complex tasks for brain informatics study can be carried out.

Ontologies are also used for the description and integration of multiple human brain data sources and grid-based data mining agents in data mining process planning [30,90,92]. It is necessary to provide:

- a formal, explicit specification for the integrated use of multiple human brain data sources in a semantic way;
- a conceptual representation about the types and properties of data/knowledge and data mining agents, as well as relations between data/knowledge and data mining agents;
- a vocabulary of terms and relations to model the domain and to specify how to view the data sources and how to use data mining agents;
- a common understanding of multiple human brain data sources that can be communicated among grid-based data mining agents.

**A Data-Brain Model and Its Construction.** The Data-Brain is a conceptual brain data model, which represents functional relationships among multiple human brain data sources, with respect to all major aspects and capabilities of HIPS, for systematic investigation and understanding of human intelligence. The Data-Brain is helpful for understanding the principles and mechanisms of HIPS [27,98,99].

The key questions are how to obtain such data by systematic fMRI/EEG experiments, how to manage such huge multimedia data for systematic investigation and understanding of human intelligence, as well as how to analyze such data from multi-aspect and multi-level for discovering new cognitive models. A new conceptual model is needed to represent complex relationships among multiple human brain data sources, which are obtained by systematic fMRI/EEG experiments. The following supporting capabilities are requested to build such a Data-Brain:

– It is a grid-based, simulation and analysis oriented, dynamic, spatial and multimedia database;
– It deals with multiple data sources, multiple data forms, multiple levels of data granularity;
– It provides multiple views and organizations;
– It includes various methods for data analysis, simulation, visualization, as well as the corresponding knowledge and models.

Agents for data collecting, storing and retrieving are deployed on the Grid platform, like Globus, as a standard Grid service. OGSA-DAI is used to build database access applications [14,102]. The aim of OGSA-DAI is to provide the middleware glue to interface existing databases, other data resources and tools to each other in a common way based on the Open Grid Services Architecture (OGSA). This middleware is based on the GGF-defined OGSI specification and layered on top of the Globus toolkit 3 OGSI implementation (GT3 Core).

Multiple data sources are collected by various cognitive fMRI/EEG experiments, modeling and transformation. They are recorded to the corresponding databases through the Grid service on the distributed sites. The data-flow is a collection of descriptions for the dynamic relationship among multiple data sources on the data-grid. Data sources from cognitive fMRI/EEG experiments, to be collected on the data-grid, include:

– human multi-perception mechanism for studying the relevance between auditory and visual information processing;
– human deductive/inductive reasoning mechanism for understanding the principle of human reasoning and problem solving in depth;
– human computation mechanism as an example of human problem solving system;
– human decision-making mechanism from developing Web based decision-making support system with an emotional factor;
– human learning mechanism for acquiring personalized student models in an interactive learning process;
– human heuristic search in problem solving and reasoning;
– human emotion factors in higher cognitive functions.

In order to build a Data-Brain, a systematic methodology of cognitive experimental design needs to be developed, so that multiple human brain data sources obtained by fMRI/EEG experiments are interrelated and utilized for multipurpose. Event-related experimental designs have become an important methodology in EEG/fMRI research to evaluate the high level characteristics of HIPS in the central nervous system [60]. There are, at present, two main methods called event-related potential (ERP) and event-related fMRI for event-related experimental designs. ERP is a tiny signal embedded in the ongoing EEG. By averaging the traces, investigators can extract this signal, which reflects neural activity that is specifically related cognitive events [21]. ERPs are best suited for addressing questions about the time course of cognition rather than elucidating the brain structures that produce the electrical events. ERPs also provide physiological indices of when a person decides to response, or when an error is detected. On the other hand, event-related fMRI follows the same logic as used in ERP/EEG studies and provides the spatial resolution. Thus, event-related fMRI will further allow fMRI and EEG to be combined in paradigms that are identical across methods. By using such techniques, it is now becoming possible to study the precise spatiotemporal orchestration of neuronal activity associated with perceptual and cognitive events [60], as well as systematic collection of human brain data for building a Data Brain.

**Multi-aspect Human Brain Data Analysis on a Multi-layer Grid.** *Multi-aspect analysis* in a multi-phase mining process is an important methodology for knowledge discovery from multiple human brain data [90]. There are two main reasons why a multi-aspect analysis approach needs to be used. First, we cannot expect to develop a single data mining algorithm for analyzing all main aspects of multiple human brain data towards a holistic understanding, due to the complexity of human brain. Various data mining agents (association, classification, clustering, peculiarity-oriented, main-fold, etc), deployed on the mining-grid, need to be cooperatively used in the multi-phase data mining process for performing multi-aspect analysis as well as multi-level conceptual abstraction and learning. Second, when performing multi-aspect analysis for complex brain informatics problems, a data mining task needs to be decomposed into sub-tasks. These sub-tasks can be solved by using one or more data mining agents that are distributed over different computers on the Grid. The decomposition problem leads us to the problem of distributed cooperative system design.

Such a methodology needs to be implemented on a wisdom Web based brain-informatics portal, which supports a multi-phase mining process based on a conceptual data model of human brain. Generally speaking, several kinds of rules and hypotheses can be mined from different data sources by multi-aspect mining. The results cannot be directly utilized to support brain scientists' research activities and applications until they are combined and refined into more general ones to form *active knowledge*, through an explanation-based reasoning process. On the other hand, from the viewpoint of applications, distributed Web inference engines under the knowledge-flow management will employ such active knowledge with various related knowledge sources together to implement knowledge services for supporting brain scientists' research activities on the brain-informatics portal [98].

In the multi-tier architecture of the brain-informatics portal, lower levels provide middleware support for higher level applications and services, thereby opening the door to developing more complex, flexible, and effective systems. The three-level workflows are generated dynamically, based on the conditions (situations), data quality analysis, and a multi-phase mining process.

We emphasize that both pre-processing and post-processing steps are important before/after using data mining agents. In particular, informed knowledge discovery, in general, uses background knowledge obtained from experts (e.g., cognitive/brain scientists) about a domain (e.g., cognitive neuroscience) to guide a spiral discovery process with multi-phase such as pre-processing, rule mining, and post-processing, towards finding interesting and novel rules/features hidden in data. Background knowledge may be of several forms including rules already found, ontologies, taxonomic relationships, causal preconditions, ordered information, and semantic categories. Such brain-informatics related knowledge, the generated hypotheses are deployed on the knowledge-grid and the knowledge-flow is utilized to generate, evaluate, refine, and employ knowledge on the knowledge-grid for various knowledge-based reasoning [68,69,95]. From the top-down perspective, the knowledge level is also the application level with the support from both the mining level and the data level to serve cognitive/brain scientists and the portal itself updating. From the bottom-up perspective, the data level supplies the data services for the mining level, and the mining level produces new rules and hypotheses for the knowledge level to generate active knowledge.

On the other hand, from the application viewpoint, distributed Web inference engines under the knowledge-flow management will utilize such active knowledge with various related knowledge sources together to implement knowledge services for supporting cognitive/brain scientists' research activities on the brain-informatics portal [68,69,98].

For a case study, our purpose is to investigate the spatiotemporal features and flow of HIPS as mentioned in Section 4.1. In our preliminary experiments, we have observed that fMRI brain imaging data and EEG brain wave data extracted from HIPS are *peculiar* ones with respect to a specific state or the related part of a stimulus. Accordingly, we proposed a way of *peculiarity oriented mining (POM)* for knowledge discovery in multiple human brain data, without using conventional imaging processing to fMRI brain images and frequency analysis to EEG brain waves [96,98]. The proposed approach provides a new way for automatic analysis and understanding of fMRI brain images and EEG brain waves to replace human-expert centric visualization. The mining process is a multi-step one, in which various psychological experiments, physiological measurements, data cleaning, modeling, transforming, managing, and mining techniques are cooperatively employed to investigate HIPS.

Further research will include studying the neural structures of the activated areas and trying to understand how a peculiar part of the brain operates and how it is linked functionally to individual differences in performance by combining various data mining methods with reasoning. Some lessons in cognitive neuroscience are applicable to novel technological developments in BI, yet others may need to be enhanced or transformed in order to manage and account for the complex and possibly more innovative practices of sharing, analyzing and creating data/knowledge that are made technically possible by the wisdom Web and knowledge grids [38,98,99].

Figure 7 gives the global picture of an example about how to investigate the spatiotemporal features and flow of HIPS. In the cognitive process from perception (e.g., a cognitive task by vision stimuli) to thinking (e.g., reasoning), data are collected in several event-related time points, and transformed into various forms in which POM centric multi-aspect data analysis (MDA) can be carried out efficiently and effectively. Furthermore, the results of separate analysis can be explained and combined into a whole flow.

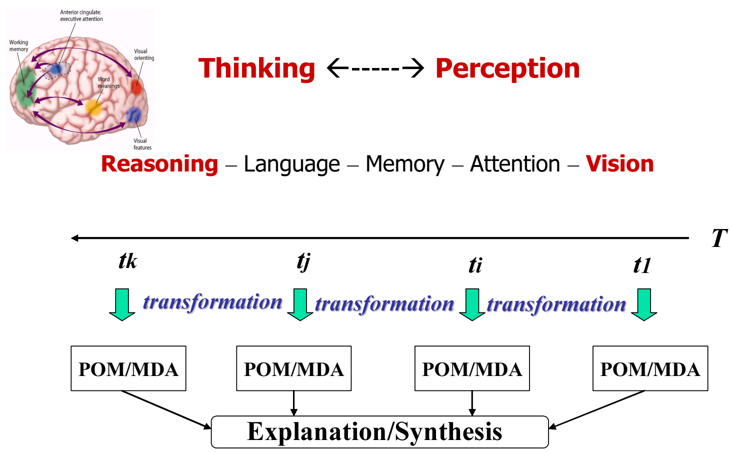


**Fig. 7.** Investigating the spatiotemporal features and flow of HIPS

## 5 Conclusion

As two related emerging fields of research, Web Intelligence and Brain Informatics mutually support each other. Their synergy will yield profound advances in the analysis and understanding of data, knowledge, intelligence and wisdom, as well as their relationships, organization and creation process. When WI meets BI, it is possible to have a unified and holistic framework for the study of machine intelligence, human intelligence, and social intelligence.

BI emphasizes on a *systematic* approach for investigating human information processing mechanisms, including measuring, collecting, modeling, transforming, managing, and mining multiple human brain data obtained from various cognitive experiments by using fMRI and EEG. In other words, human brain is regarded as an information processing system, and a *systematic* study including the investigation of human thinking centric mechanisms, the design of cognitive experiments, data management, and data analysis. Multi-aspect analysis in multiple human brain data sources based on a data brain model is an important methodology in BI.

The proposed methodology attempts to change the perspective of cognitive/brain scientists from a single type of experimental data analysis towards a holistic view at a long-term, global field of vision to understand the principles and mechanisms of HIPS. New generations of WI research and development need to understand multi-nature of intelligence in depth. The recently designed instrumentation (fMRI etc.) and advanced IT are causing an impending revolution in both WI and BI, making it possible for us to understand and develop human-level Web intelligence.

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