Data-Brain Modeling for Systematic Brain Informatics

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Abstract. In order to understand human intelligence in depth and find the cognitive models needed by Web Intelligence (WI), Brain Informatics (BI) adopts systematic methodology to study human "thinking centric" cognitive functions, and their neural structures and mechanisms in which the brain operates. For supporting systematic BI study, we propose a new conceptual brain data model, namely Data-Brain, which explicitly represents various relationships among multiple human brain data sources, with respect to all major aspects and capabilities of human information processing systems (HIPS). On one hand, constructing such a Data-Brain is the requirement of systematic BI study. On the other hand, BI methodology supports such a Data-Brain construction. In this paper, we design a multi-dimension framework of Data-Brain and propose a BI methodology based approach for Data-Brain modeling. By this approach, we can construct a formal Data-Brain which provides a long-term, holistic vision to understand the principles and mechanisms of HIPS.

1 Introduction

Brain Informatics (BI) [13,14] is a new 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 Web Intelligence (WI) and data mining centric advanced information technologies. It can be regarded as brain sciences in the WI centric IT age [12,14].

The capabilities of human intelligence can be broadly divided into two main aspects: perception and thinking. Though it is not appropriate to say that thinking centric cognitive functions are superior to perception oriented functions, thinking centric functions obviously reflect more intelligence of HIPS than perception oriented functions. Thus, for getting cognitive models needed by WI, our BI study focuses on the "thinking centric" cognitive functions, which are complex and involved with multiple inter-related cognitive functions with respect to activated brain areas for a given task, and neurobiological processes of

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spatio-temporal features related to the activated areas. Aiming at the characteristics of thinking centric functions, 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 (functional magnetic resonance imaging) and EEG (electroencephalogram).

Such systematic study includes four core issues: systematic investigation of human thinking centric mechanisms, systematic design of cognitive experiments, systematic human brain data management, and systematic human brain data analysis and simulation. For supporting this systematic study, BI attempts to capture new forms of collaborative and interdisciplinary work. New kinds of BI methods and global research communities will emerge, through infrastructures on the Wisdom Web[11] and knowledge grids, that enable high speed and distributed, agent-based large-scale analysis, simulations and computations, and radically new ways of sharing data and knowledge.

A BI portal [12] is just such an infrastructure which implements data storage, sharing, and utilization with a long-term, holistic vision for systematic data management. It is oriented to analysis and simulation, so conceptual modeling of brain data, i.e., Data-Brain modeling [2], is a core issue in BI portal construction. Systematic BI methodology also supports such a Data-Brain construction.

This paper presents a case study on Data-Brain modeling based on BI methodology. The rest of this paper is organized as follows. Section 2 discusses background and related work. Section 3 gives the definition of Data-Brain and its multi-dimension framework. Section 4 describes a BI methodology based approach for Data-Brain modeling. Finally, Section 5 gives concluding remarks.

2 Background and Related Work

As a typical "data" science, the key questions of recent Brain Informatics study are how to obtain high quality of experimental data, how to manage such huge multimedia data, as well as how to analyze such data for discovering new brain related knowledge. Effective data management is the base of BI study. Over the last decade, researchers have focused their efforts on constructing various brain databases for supporting brain data management. These brain databases can store microcosmic structure data [21] and macroscopic structure data [16], respectively. As two kinds of important macroscopic brain data, both fMRI and EEG are also focused. The researchers constructed many related brain databases, such as fMRIDC [18], AED [15], all of which are oriented to data storage and sharing.

The construction of traditional databases often adopts a top-down course, from conceptual modeling to physical modeling. But in the existing studies of brain databases, conceptual modeling of brain data is often neglected. Because most of data in the existing brain databases come from separated studies, the relationships among data are lack. Conceptual modeling can only be used to describe the limited relationships among data in the same experiment task, so it cannot get enough attention. Because of the neglect of conceptual data modeling, it is difficult to support systematic BI study based on these brain databases since the relationships among data cannot be explicitly represented and applied. For example, systematic data analysis needs to adopt agent-enriched human brain data mining for multi-aspect analysis and simulation on multiple human brain data sources. This needs not only systematic data storage based on the relationships among data, but also a formal conceptual model which explicitly describes the relationships among data to guide agent computing. Hence, systematic BI methodology needs the study of conceptual modeling of brain data, i.e., Data-Brain modeling.

The complexity of human brain leads that BI study needs global cooperation. Thus, more and more researchers focus their efforts on connecting decentralized brain databases by network or grid infrastructure to construct various resource networks/grids for supporting global cooperation. The international neuroinformatics network is just such a resource network, which contains many brain database nodes, such as Brain Bank [17]. At the network/grid level, conceptual data models have the wider scope of applications, including not only off-time applications, such as supporting the design of database schemas, but also on-time applications, such as providing formal knowledge sources. Obviously, the traditional graphical modeling languages, such as the Entity-Relationship (ER) model [1], cannot meet all the requirements of new applications.

At present, ontologies are widely applied on network/grid based systems [6]. Both ontologies and data models are partial accounts of conceptualizations [9], and the common features between them have gotten attention [5]. Though some researchers focus on differentiating ontologies from conceptual data models [4], the various applications of ontologies, especially the applications in resource networks/grids, still make the ontology be a new effective approach for formally modeling data related domain knowledge at the conceptual level. Hence, ontology can be regarded as a new approach of conceptual data modeling at the network/grid level.

3 Data-Brain

3.1 What Is a Data-Brain?

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. On one hand, developing such a Data-Brain is a core research issue of BI. Systematic BI study needs a Data-Brain to describe multi-aspect data related knowledge for supporting systematic data storage, sharing, and utilization. Based on this way, it provides a long-term, holistic vision to uncover the principles and mechanisms of underlying HIPS. On the other hand, BI methodology supports such a Data-Brain construction. As a network/grid level of conceptual data model, the Data-Brain can adopt an ontological modeling approach based on BI methodology. In other words, the Data-Brain goes beyond specificity of a certain application and straightly models related domain knowledge based on multiple core issues of BI methodology, including systematic investigation, systematic experimental design, systematic data storage (the base of systematic data management), and systematic data analysis and simulation.

3.2 A Multi-dimension Framework of Data-Brain

Based on systematic BI methodology, we design a multi-dimension framework of Data-Brain as shown in Fig. 1, including four dimensions and multiple conceptual views. We only give two conceptual views, the reasoning centric view and the computation centric view, as examples in Fig. 1 because of the limitation of space.

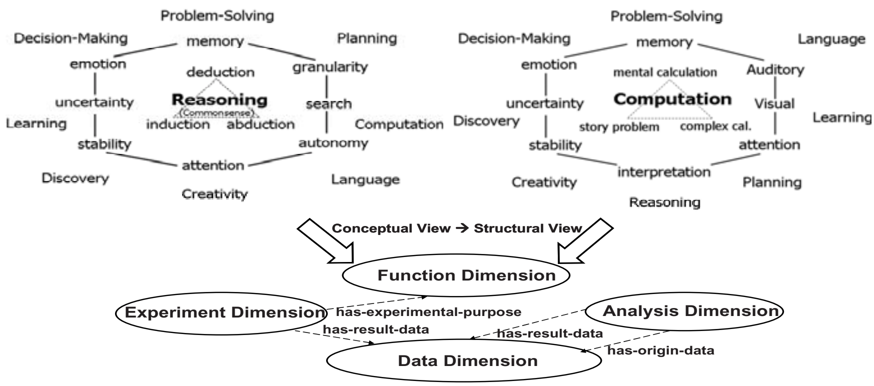

Fig. 1. A multi-dimension framework of Data-Brain

Firstly, the Data-Brain provides multiple conceptual views of systematic investigation of human thinking centric cognitive functions. The capabilities of human intelligence can be broadly divided into two main aspects: perception and thinking. Our BI study focuses on the "thinking centric" cognitive functions, which are complex and closely related to each other. Thus, we need to construct various conceptual views which illustrate systematic BI investigation and their inter-relationships from different viewpoints based on functional relationships among related human cognitive functions. These conceptual views can be regarded as cognitive/brain scientists' interfaces to facilitate their own research activities and cooperation with different focusing and research issues.

Figure 2 gives an abstract representation of the conceptual view, which illustrates reasoning centric, thinking oriented BI investigation and their inter-relationships based on functional relationships among related human cognitive functions. The core issue is to investigate human deduction, induction, and abduction related reasoning mechanisms, as well as including commonsense reasoning, as shown in the central of Fig. 2. Heuristic search, attention, emotion and memory are some component functions to implement human reasoning, as well as (information) granulation, autonomy, stability and uncertainty are some interesting characteristics, which need to 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.

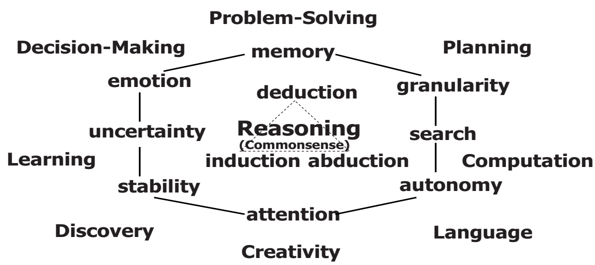

Fig. 2. The "Reasoning" centric conceptual view

Secondly, the conceptual view of the Data-Brain can be transformed into its own structural view with four dimensions, namely function dimension, data dimension, experiment dimension, and analysis dimension, respectively. Figure 1 illustrates such a transformation. Here we give more descriptions on the four dimensions as follows:

- The **function dimension** is a conceptual model of domain knowledge aiming at the systematic investigation in BI methodology. It describes the information processing courses of human thinking centric cognitive functions and functional relationships among them at the conceptual level. As stated above, the thinking centric cognitive functions are complex and closely related to each other, so Data-Brain needs to include a function dimension. The function dimension provides a holistic, conceptual functional model of human brain for systematic BI study. It also provides a machine-readable knowledge base for constructing various conceptual views.
- The **data dimension** is a conceptual model of domain knowledge aiming at systematic brain data storage. It describes multiple views, schemes, and organizations of human brain data with multiple data sources, multiple data forms, multiple levels of data granularity at the conceptual level. Conceptual modeling heterogeneous brain data using the data dimension is the key to realize systematic data storage which is the base of the systematic data management in BI methodology. By relations with the function dimension, the data dimension provides a conceptual data model which represents functional relationships among multiple human brain data sources obtained from various cognitive experiments with respect to all major aspects and capabilities of HIPS. This kind of data representation is with multi-level by modeling,

abstracting and transforming for multi-aspect analysis and simulation. The data dimension supports the implementation of a grid-based, analysis and simulation oriented, dynamic, spatial and multimedia database for storing and sharing the heterogeneous brain data efficiently and effectively.

– The **experiment dimension** is a conceptual model of domain knowledge aiming at the systematic experimental design in BI methodology. It describes characteristics of various experimentation plans, their classification and inter-relationships at the conceptual level. Systematic experimental design is an important issue of BI methodology. For uncovering the principles and mechanisms of HIPS, BI researchers need to design a series of cognitive experiments to obtain high quality of experimental data, which represent different aspects of various thinking centric cognitive functions, based on systematic methodology of cognitive experimental design. Thus, Data-Brain needs to include an experiment dimension. By relations with the function dimension and data dimension, the experiment dimension explicitly describes various relationships among various data sources. By the experiment dimension, cognitive experiments related information can be stamped on each data set for supporting systematic data analysis and simulation.
– The **analysis dimension** is a conceptual model of domain knowledge aiming at the systematic data analysis and simulation in BI methodology. It describes characteristics of various analysis and simulation methods, as well as their relationships with multiple human brain data for multi-aspect analysis and simulation. Agent-enriched data mining for multi-aspect data analysis is an important issue of BI methodology because the brain is too complex for a single data mining algorithm to analyze all the available data. Thus, Data-Brain needs to include an analysis dimension. Based on the analysis dimension corresponding to the data and experiment dimensions, various methods for data processing, mining, reasoning, and simulation can be deployed as agents on a multi-phase process for performing multi-aspect analysis as well as multi-level conceptual abstraction and learning, which aims at discovering useful knowledge to understand human intelligence in depth [12].

As shown in Fig. 1, these dimensions are not isolated from each other, but with various relations among them.

4 Data-Brain Modeling

4.1 Data-Brain Modeling Based on Brain Informatics Methodology

As a network/grid level of conceptual data model, Data-Brain modeling can adopt an ontological modeling approach. Comparing with other ontology engineering methodologies, the "Enterprise Methodology" [8] especially focuses on the construction of concept hierarchy and more fit to construct a Data-Brain which take concept hierarchies as skeletons of dimensions. Thus, we choose it to construct a Data-Brain. The course mainly includes the following four steps:

– defining the domain and scope of a Data-Brain
– identifying key concepts and properties
– defining the concept hierarchy through taxonomic relations
– constructing axioms

All of the above work, from the identification of key concepts to the classification of concepts, needs to obey some rules. During Data-Brain modeling, these rules come from systematic BI methodology, i.e., Data-Brain modeling is based on BI methodology.

According to dimension definitions, different dimensions of a Data-Brain focus on different aspects of data related domain knowledge. Thus, after defining BI as the domain of Data-Brain and the domain knowledge about BI data as the scope of Data-Brain, we can follow the remanent three steps of "Enterprise Methodology" to respectively construct four dimensions of Data-Brain based on the different issues of BI methodology, including:

– constructing the function dimension based on the systematic investigation
– constructing the data dimension based on the systematic data storage
– constructing the experiment dimension based on the systematic experimental design
– constructing the analysis dimension based on the systematic data analysis and simulation.

In the next section, we will describe how to construct the function dimension using OWL-DL language [19] and protege tool [20], which can be regarded as an example of the BI methodology based dimension construction.

4.2 Constructing the Function Dimension Based on Systematic Investigation

The function dimension constructed by ontology is an ontology of human cognitive functions. At present, most of human brain related ontologies are the brain structure related ontologies, such as the ontology of brain cortex anatomy [3]. The study about the ontology of cognitive functions has not gotten attention.

The systematic investigation is an important issue in BI methodology. Based on it, the course of function dimension construction can be described as follows:

– **Identifying key concepts and properties**: The systematic investigation in BI methodology is the investigation of human thinking centric mechanisms. Thus, key concepts of the function dimension are human cognitive function concepts, such as "Reasoning" and "Problem-solving", and their sub-function concepts, such as "Induction". These key concepts are described by properties, including data properties and object properties. The data properties are used to describe concepts themselves; the object properties are used to describe relationships among concepts. In this systematic investigation, each cognitive function concept represents a series of study activities which aim at the cognitive function. So it is worthless to describe cognitive function concepts themselves in the function dimension. For providing a holistic study view and functional model of human brain, the function dimension needs to focus on functional relationships among cognitive functions. Thus, there is no key data property in the function dimension. Only the key object property "has-functional-relationship-with", which describes functional relationships among cognitive functions, is included in function dimension. It includes various sub-properties, such as "includes-in-function" and "related-to-in-function", which are used to describe different functional relationships.

- **Defining the concept hierarchy**: At present, there is not standard taxonomy of human cognitive functions. Researchers often classify cognitive functions according to their own study viewpoints, such as LRMB model [10]. The systematic investigation in BI methodology is a thinking centric one, so we can define the concept hierarchy of function dimension as follows. Firstly, human cognitive function concepts are classified into two classes, "Perception-Centric-Cognitive-Function" and "Thinking-Centric-Cognitive-Function". The former includes perception oriented cognitive functions related concepts, such as "Vision" and "Hearing". The latter includes thinking centric cognitive functions related concepts on which BI focuses, such as "Reasoning". Secondly, all of cognitive functions are specialized into more characterized sub-classes. For example, the concept "Reasoning" can be specialized into multiple sub-concepts, such as "Induction" and "Deduction".
- **Constructing axioms**: Axioms are formal assertions that model sentences that are always true. They provide a way of representing more information about concepts, such as constraining on their own internal structure and mutual relationships. The primary axioms in Data-Brain are restriction axioms, including value constraints and cardinality constraints. Thus, constructing axioms in Data-Brain can be specialized as using data properties and object properties to describe concepts with the necessary constraints. Because of lacking data properties, constructing axioms in function dimension is just to use the key object property "has-functional-relationship-with" and its sub-properties to describe cognitive function concepts of function dimension with the necessary constraints. For example, we can use the object property "includes-in-function" to describe the concept "Induction" as follow:

  $$Induction \subseteq Restriction(\exists\, includes-in-function\ Attention).$$

  This means that *Induction* includes *Attention* as a sub-component, but it does not only include *Attention*.

4.3 Constructing Conceptual Views

A Data-Brain includes various conceptual views which are extracted from the function dimension of the Data-Brain. Because we use ontologies to model Data-Brain, its conceptual views are just the traversal views [7] of the function dimension and can be defined based on the definition of traversal view. Firstly, we give some related definitions:

Definition 1. *A* **View Core***, denoted by $Core$, is a thinking centric cognitive function concept in the function dimension. As the core of a conceptual view, it is corresponding to a BI study issue and represents all the study activities of this issue.*

Definition 2. *A* **Traversal Directive** *for the source ontology O, denoted by TD, is a pair:*

$$< C_{st}, RT >,$$

where C_{st} is a concept in the source ontology O from which view is extracted, and represents the starter concept of the traversal; $RT =< R, n >$ is a relation directive, where R is a relation in O and n is a nonnegative integer or infinity which specifies the depth of the traversal along the relation R. If $n = \infty$, then the traversal includes a transitive closure for R starting with C_{st}.

Definition 3. *A* **Traversal Directive Result** *(the result of applying directive TD to O), denoted by $TD(O)$, is a set of concepts from the source ontology O such that:*

1. *$TD =< C_{st}, RT >$;*
2. *$RT =< R, n >$, $n > 0$. if C_{st} is a concept in the starts of the relation R, and a concept $C \in O$ is the corresponding end of the relation R, then C is in $TD(O)$;*
3. *$RT_{next} =< R, n-1 >$ is a relation directive. if $n = \infty$, then $n-1 = \infty$. For each concept F that was added to $TD(O)$ in step 2, the traversal directive result $TD_F(O)$ for a traversal directive $TD_F =< F, RT_{next} >$ is in $TD(O)$.*

No other concepts are in $TD(O)$.

Based on the above definitions, the conceptual view of a Data-Brain can be defined as follows:

Definition 4. *A* **Conceptual View***, denoted by CV, is a five-tuple:*

$$(Core, CF, CFIC, RF, R),$$

where

- *$CF =< Core, < parentClassOf, \infty >> (FD)$ is a specialization of $TD(O)$ and represents the concept set of core cognitive functions in a conceptual view, where "$parentClassOf$" is the inverse relation of the relation "subClassOf", and FD is the function dimension of a Data-Brain;*
- *$CFIC =< Core, < includes\text{-}in\text{-}function, \infty >> (FD)$ is a specialization of $TD(O)$ and represents the concept set of component cognitive functions and interesting characteristics in a conceptual view, where "includes-in-function" is a relation in the function dimension and used to describe the functional part-whole relationship among cognitive functions;*

Algorithm 1. Conceptual View Construction

Input: $Core$ and FD.
Output: CV.
1. Initialize empty concept sets $CV.CF$, $CV.CFIC$ and $CV.RF$;
2. Set $CV.Core = Core$;
3. Set $CV.R = \{$"$parentClassOf$", "$includes\text{-}in\text{-}function$", "$related\text{-}to\text{-}in\text{-}function$"$\}$;
4. $CV.CF = TDR(Core,$"$parentClassOf$"$, \infty, FD)$;
5. $CV.CFIC = TDR(Core,$"$includes\text{-}in\text{-}function$"$, \infty, FD)$;
6. $CV.RF = TDR(Core,$"$related\text{-}to\text{-}in\text{-}function$"$, \infty, FD)$;
7. return CV

Algorithm 2. Getting Traversal Directive Result: TDR

Input: C_{st}, R, n, and O.
Output: $Concepts$.
1. Initialize an empty set of result concepts, $Concepts$;
2. Initialize the depth of the traversal, $depth = n$;
3. If $(depth == 0)$ then
4.   return $Concepts$;
5. $depth_{next} = depth$;
6. If $(depth_{next} <> \infty)$ then
7. $depth_{next} = depth_{next} - 1$;
8. If ($R ==$ "$parentClassOf$") then
9.   For each class c_i in O
10.   If (c_i $subClassOf$ C_{st}) then
11.   Add c_i into $Concepts$;
12.   Add $TDR(c_i, R, depth_{next}, O)$ into $Concepts$;
13.   End If
14.   End For
15. Else
16.   For each $Restriction$ in C_{st}
17.   If ($Restriction$ is a value constraint *and* its property name $== R$) then
18. $c_i =$ Range of $Restriction$;
19.   Add c_i into $Concepts$;
20.   Add $TDR(c_i, R, depth_{next}, O)$ into $Concepts$;
21.   End If
22.   End For
23. End If
24. return $Concepts$

– $RF =< Core, < related\text{-}to\text{-}in\text{-}function, \infty >> (FD)$ *is a specialization of* $TD(O)$ *and represents the concept set of related cognitive functions in a conceptual view, where "*$related\text{-}to\text{-}in\text{-}function$*" is a relation in the function dimension and used to describe the functional pertinence among cognitive functions*

– $R = \{parentClassOf, includes\text{-}in\text{-}function, related\text{-}to\text{-}in\text{-}function\}$ *is a set of relations which are used to construct the conceptual view.*

According to the above definitions, the algorithm for extracting a conceptual view from an OWL-DL based Data-Brain is shown in Algorithm 1. Its input parameters are the view core $Core$ and the function dimension FD. Its output is the $Core$ centric conceptual view CV. The function TDR shown in Algorithm 2 is used to get the traversal directive result. Its input parameters are C_{st}, R, n, and O, which are corresponding to the starter concept, the name of relation, the depth of the traversal, and the source ontology of the definition of traversal directive result, respectively.

Using the above algorithms, we can choose different cognitive function concepts as view cores to construct various conceptual views based on various viewpoints of BI investigation.

5 Conclusions

The Data-Brain modeling is a core issue of BI study. Aiming at the requirements of systematic data management, this paper proposes a new conceptual data model of brain data, called Data-Brain. By the BI methodology based approach of Data-Brain modeling, a multi-dimension, formal Data-Brain can be constructed. It will be the core component of BI portal and play an important role in systematic BI study by providing the following functions:

– A formal conceptual model of human brain data, which explicitly describes the relationships among multiple human brain data, with respect to all major aspects and capabilities of HIPS, for supporting systematic human brain data storage, integration and sharing;
– A knowledge-base of systematic BI study, which stores brain data related multi-aspect domain knowledge to both support various knowledge driven data applications and provide valuable knowledge sources for solving special domain problems, such as the diagnosis and treatment for MCI (mild cognitive impairment) patients;
– A global view and knowledge framework for constructing a BI portal, on which various methods for data processing, mining, reasoning, and simulation are deployed as agents for implementing the Data-Brain driven multi-aspect data analysis.

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21. Olfactory Receptor DataBase, `http://senselab.med.yale.edu/ORDB/default.asp`