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Application Of Intelligent data agent in data mining problems

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ABSTRACT

An agent-enriched peculiarity-oriented mining approach demonstrates the brain informatics methodology by transforming and mining human-brain data obtained from cognitive event- related potential experiments. To understand human intelligence in depth, we must first master the brain's operation mechanisms. Ignoring the brain's activity and focus-ing instead on behavior has seriously impeded our ability to understand how human beings accomplish complex adaptive and distributed problem-solving.

Introduction:

Research from the last decade on how humans process information has led to advances in measurement and analysis technologies. Recently, researchers have introduced various noninvasive brain functional measurements, including event-related potential/electroencephalography (ERP / EEG) and functional magnetic resonance imaging (fMRI). Systematically analyzing this measurement data lets us clarify the relationship between a state and an activity. We can also use such measurement and analysis to develop more advanced human cognitive models. Hence, new instrumentation and data analysis methods are creating a revolution in both AI and brain sciences. The synergy between the two fields promises to yield pro- found advances in our understanding of intelligence over the coming decade.3,6,7

Brain informatics (BI) is a new interdisciplinary field that systematically studies the human information-processing mechanism from macro and micro viewpoints. It does this using experimental, computational cognitive neuroscience technologies and Web-intelligence- centric advanced information technology. In particular, BI attempts to understand human intelligence in depth to support a long-term, holistic vision to uncover the principle and mechanisms underlying human information- processing systems (HIPS).

The ability to perform large-scale analysis and simulation of brain data will shape BI's future. Current research focuses on two key questions:

• How can we design psychological and physiological experiments to systematically obtain various data from HIPS?

• How can we manage and analyze such data from multiple viewpoints to discover new models of HIPS?

Researchers have developed expert tools— such as the Brain Vision Analyzer and MEDx with statistical parametric mapping—for cleaning, normalizing, and visualizing ERP and fMRI data, respectively. They've also studied how to analyze and understand ERP and fMRI data using data mining and statistical learning techniques.3-5,8 To understand human information processing (IP) principles and mechanisms relating to higher cognitive functions such as problem solving, reasoning, and learning we must develop new brain data-mining techniques based on the BI methodology. The human brain is too complex for a single data mining algorithm. Agent enriched brain data mining for multi-aspect data analysis is thus a key BI methodology for analyzing all available cognitive experimental data. We've developed an agent-enriched peculiarity-oriented mining (A-POM) approach for multi-aspect ERP data analysis. We present our approach here, along with a case study that demonstrates the BI methodology.

Overview: Brain Informatics Methodology:

Researchers have traditionally studied brain sciences using various disciplines, including cognitive science and neuroscience. BI, however, represents a shift in brain research. We can regard BI as brain sciences in the Web- intelligence-centric IT age, 2 ,6,7 studying the human brain from the informatics viewpoint that is, studying the brain as a HIPS.

BI researchers use informatics to support brain science studies and at- tempt to capture new forms of collaborative and interdisciplinary work. Thus, new kinds of BI methods and global research communities will emerge through the wisdom Web, an enormous, intelligent organism that will use data, information, knowledge, and a wisdom hierarchy to move toward human level web intelligence reality.9 These new BI methods will incorporate knowledge grids, which will enable high speed, large-scale, distributed agent-based analysis and computations, as well as radical new ways of sharing data and knowledge. Despite these changes, lessons from both cognitive science and neuroscience remain applicable to BI's novel technological developments. 2 ,6,10

BI emphasizes a systematic approach to investigating human IP mechanisms, including measuring, collecting, modeling, transforming, managing, and mining brain data obtained from various cognitive experiments. Such systematic study currently focuses on four main research questions:

How do thinking- centric brain mechanisms work?

How can we best design cognitive experiments?

How can we manage brain data in an integrated way? How can we analyze brain data deeply and systematically?

In the first case, we can broadly divide the capabilities of human intelligence into two main aspects: perception and thinking. Cognitive neuroscience researchers have achieved advanced results in perception-oriented studies, but have reported only a few separate, preliminary studies that were thinking-oriented or focused on the overall human IP process.11 Systematic investigation of thinking-centric mechanisms is therefore based on both Web intelligence research and state-of-the- art cognitive neuroscience.1,2 ,7,11,12

Second, to systematically design cognitive experiments, we must design tasks for both psychological and physiological experiments. From these, we can systematically obtain HIPS data for use in multipurpose investigations of human thinking- and perception- centric cognitive functions. To dis- cover new knowledge and models of human IP activities, we must use multiple data sources and practical measuring methods, such as ERP and fMRI. Furthermore, we must systematically design cognitive experiments so the resulting data is useful for multiple purposes.

Third, we can investigate how to manage the brain data by using a conceptual brain data model. This model represents functional relationships among multiple brain data sources with respect to all major HIPS aspects and capabilities. Such data representation offers multilevel modeling, abstraction, and transformation for multi-aspect analysis and simulation.

Finally, to systematically examine how to analyze the brain data deeply, we can extract significant patterns and features from multiple brain data sources obtained by using powerful tools, such as ERP and fMRI, and then engage in multi-aspect data analysis by combining various data mining and reasoning methods.3,5,6,12 We can also deploy agents for data preprocessing, mining, reasoning, and simulation in a multiphase process to achieve multi-aspect analysis and multilevel conceptual abstraction and learning.

By addressing each of these key re- search areas, the BI framework com- bines analysis and simulation to understand human intelligence in depth; agent-enriched data mining will play a central role in its multiphase process.

Case Study:
Agent-Enriched Peculiarity-Oriented Mining:

Our work focuses on human IP activities at two levels: spatiotemporal features and flow based on functional relationships among activated brain areas for various tasks; and the neural structures and neurobiological processes related to those activated areas. More specifically, we're trying to understand how neurobiological processes support a cognitive process based on BI methodology. We're thus investigating how a specific part of the brain operates at a specific time, how those operations change over time, and how the activated areas work cooperatively to implement an overall IP system.

As a step in this direction, we're studying ERP data. Such data is peculiar with respect to a specific state or the related part of a stimulus. To automate ERP data analysis and understanding, we propose the A-POM knowledge-discovery approach. A-POM doesn't use conventional ERP analysis and doesn't require human-expert-centric visualization.6 Instead, it investigates the human IP mechanism through a multistep mining process that cooperatively employs various psychological experiments, physiological measurements, data cleaning, modeling, transforming, managing, and mining techniques.

A-POM has two main benefits for addressing the complexity and diversity of brain data and applications:

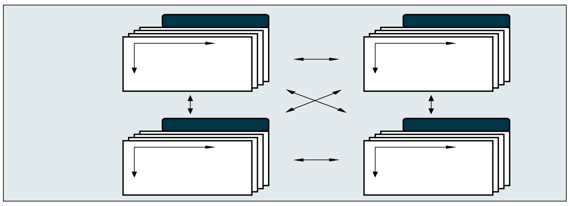

Fig. 1: A-POM knowledge-discovery approach

A-POM agents cooperate in a multiphase process and support multilevel conceptual abstraction and learning. Researchers can apply our methodology to interpret a HIPS's spatiotem-poral features and flow. In the cognitive process from perception (in our case, a cognitive task stimulated by vision) to thinking (computation), the A-POM system collects data from several event-related points in time and transforms them into various forms suitable for multi-aspect data analysis. The system then explains the results of the separate analyses and synthesizes them into an overall flow.

Multi-aspect ERP Data analysis:

We identified the best use of each feature using two aspects of ERP data analysis—the potential change and the frequency element—and experiments with multiple difficulty levels. A-POM can also find interesting temporal and spatial features in ERP data using the potential change and frequency aspects. It's clear that a specific brain section operates in a specific time and those operations change over time. Al- though it's easy to detect ERP data's concavity and convexity (P300 and so on) using an existing tool, it's difficult to find peculiar data when there are

The first property relates to the objects' distance or dissimilarity. Intuitively speaking, an object is different from other objects if it's regarded as far away from them on the basis of certain distance functions. The peculiar object's attribute values must differ from those of other objects. We can therefore define distance between objects based on the distance between their values.

The second property relates to the notion of support. Peculiar data's support must be low frequency. The brain doesn't directly compare one object to another; it first recognizes objects by comparing them to stored representations.19 However, as we describe later, we use a simplified method of comparison.

We use each cognitive experiment's resulting data for multiple purposes, in keeping with the BI methodology. Our experiments might, for example, satisfy the requirements for investigating the mechanisms of human visual and auditory systems, computation, problem solving (that is, we regard the computation processing as an example of problem-solving processes), and HIPS general spatiotemporal features and flow.

Furthermore, we set up two types of cognitive experiments with respect to a series of computation tasks. The two types differ in terms of visual attention:

•Type A: numbers remain on the screen.

•Type B: the subjects must continue to remember numbers while the numbers on the screen change.

We've applied the A-POM-based approach to all ERP channels with multiple difficulty levels for finding peculiar channels and peculiar time bands. We obtained some remarkable results by comparing results from Type A and Type B experiments.

As an example of human-expert-centric visualization, Figure 4 shows a computation process's spatiotemporal feature, represented by Type A and Type B topographies. We obtain these topographies by adding the average of seven subjects using an ordinary EEG analysis tool. When human experts read such figures, they naturally note the points of the noticeable positive and negative potentials in a spatiotemporal mode.

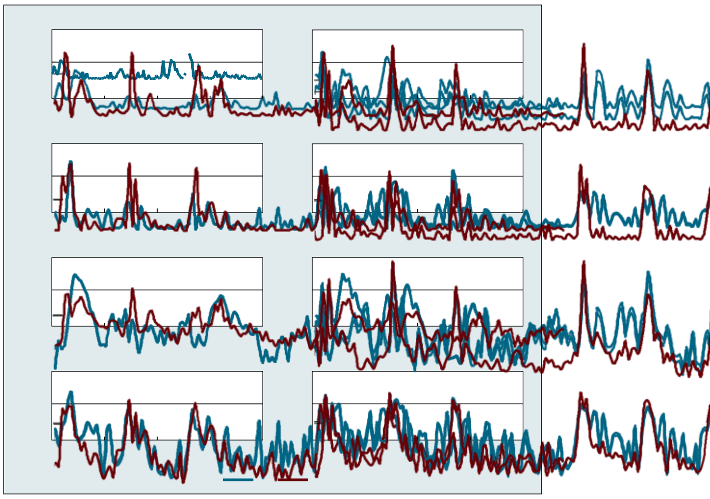

Fig. 2: Examples of agent-enriched peculiarity-oriented mining (A-POM) analysis. Two example channels

Experimental Results:

In this work, explaining and integrating our A-POM-based multi-aspect analysis results is a key issue. We do this in four distinct steps. First, we examine an integrated model of the results in relation to spatiotemporal features. As Figure 2 shows, we use an example of computation processing from the macro viewpoint, which consists of several component functions of the human computation mechanism, including attention, interpretation, short- term memory, understanding of work, computation, and checking. We use each cognitive experiment's resulting data for multiple purposes, in keeping with the BI methodology.

References:

1. R. Morris, L. Tarassenko, and M.Kenward, eds., Cognitive Systems: Information Processing Meets Brain Science, Elsevier, 2006.
2. N. Zhong, "Impending Brain Informatics (BI) Research from Web Intelligence (WI) Perspective," Int'l J. Information Technology and Decision Making, vol 5, no. 4, 2006, pp. 713 –727.
3. T.M. Mitchell et al., "Predicting Hu- man Brain Activity Associated with the Meanings of Nouns," Science, vol. 320, 2008, pp. 1191–1195.
4. T.C. Handy, Event-Related Potentials, A Methods Handbook, MIT Press, 2004.
5. F.T. Sommer and A. Wichert, eds., Exploratory Analysis and Data Modeling in Functional Neuroimaging, MIT Press, 2003.
6. N. Zhong and S. Motomura, "WI Based Multi-Aspect Data Analysis in a Brain Informatics Portal," Autonomous Intelligent Systems: Agents and Data Mining, V. Gorodetsky et al., eds., LNAI 4476, Springer, 2007, pp. 46 –59.
7. N. Zhong et al., "Web Intelligence Meets Brain Informatics," N. Zhong et al., eds., Web Intelligence Meets Brain Informatics, LNAI 4845, Springer,
8. 2007, pp. 1–31.

9. N. Zhong et al.,"Peculiarity Oriented fMRI Brain Data Analysis for Studying Human Multi-Perception Mechanism," Cognitive Systems Research, vol. 5, no.
10. 3, Elsevier, 2004, pp. 241–256.
11. N. Zhong, J. Liu, and Y.Y. Yao, "En- visioning Intelligent Information Technologies through the Prism of Web Intelligence," Comm. ACM, vol. 50, no.3, 2007, pp. 89–94.
12. N. Zhong et al., "Building a Data Mining Grid for Multiple Human Brain Data Analysis," Computational Intelligence, vol. 21, no. 2, Blackwell, 2005, pp. 177–196.
13. M.S. Gazzaniga, ed., The Cognitive Neurosciences III, MIT Press, 2004.
14. J.R. Anderson, How Can the Human Mind Occur in the Physical Universe? Oxford Univ Press, 2007.
15. H. Nittono et al., "Event-Related Potential Correlates of Individual Differences in Working Memory Capacity," Psychophysiology, vol. 36, no. 6, 1999, pp. 745–754.
16. G. Dong and J. Li, "Efficient Mining of Emerging Patterns: Discovering Trends and Differences," Proc. 5th Int'l Conf. Knowledge Discovery and Data Mining (KDD 99), AAAI Press, 1999, pp.43 –52.
17. A.A. Freitas, "On Objective Measures of Rule Surprisingness," J. Zytkow and M. Quafafou, eds., Principles of Data Min- ing and Knowledge Discovery, LNAI 1510, Springer, 1998, pp. 1–9.
18. E. Suzuki, "Autonomous Discovery of Reliable Exception Rules," Proc. 3rd Int'l Conf. Knowledge Discovery and Data Mining (KDD 97), AAAI Press, 1997, pp. 259–262.
19. N. Zhong, Y.Y. Yao, and M. Ohshima, "Peculiarity