An Investigation of Human Problem Solving System: Computation as an Example

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Abstract. Although human problem solving has been investigated in a behavior based approach, it has been recognized that ignoring what goes on in human brain and focusing instead on behavior has been a large impediment to understand how human being does complex adaptive, distributed problem solving and reasoning. In the paper, we propose a methodology for investigating human problem solving process by combining ERP mental arithmetic tasks, as a case study, with multi-aspect data analysis. Preliminary results show the usefulness of our methodology.

1 Introduction

Problem-solving is one of main capabilities of human intelligence and has been studied in both cognitive science and AI [9], where it is addressed in conjunction with reasoning centric cognitive functions such as attention, control, memory, language, reasoning, learning, and so on, using a logic based symbolic and/or connectionist approach. Although logic based problem-solving is "perfect", mathematical systems with no real time and memory constraints, Web-based problem-solving systems need real-time and dealing with global, multiple, huge, distributed information sources.

Furthermore, 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 [3,11,12,13,17]. In other words, ignoring what goes on in human brain and focusing instead on behavior has been a large impediment to understand how human being does complex adaptive, distributed problem solving and reasoning.

In the light of Brain Informatics [16,17], we need to investigate specifically the following issues:

- What are the existing problem-solving models in AI, cognitive science, and neuroscience?
- How to design fMRI/EEG experiments and analyze such fMRI/EEG data to understand the principle of human problem solving in depth?

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– How to build the cognitive model to understand and predict user profile and behavior in a problem solving process?
– How to implement human-level problem solving on the Web based portals that can serve users wisely?

As a result, the relationships between classical problem solving and biologically plausible problem solving need to be defined and/or elaborated [17].

As a step in this direction, we observe that fMRI brain imaging data and EEG brain wave data extracted from human problem solving system are peculiar ones with respect to a specific state or the related part of a stimulus. Based on this point of view, we propose 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. 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 human problem solving system.

The rest of the paper is organized as follows. Section 2 provides a mining process for multi-aspect human brain data analysis of human problem solving system. Sections 3 and 4 explain how to design the experiment of an ERP mental arithmetic task with visual stimuli, and describe how to do multi-aspect analysis in the obtained ERP data, respectively, as an example to investigate human problem solving and to show the usefulness of the proposed mining process. Finally, Section 5 gives concluding remarks.

2 A Mining Process for Multi-aspect Human Brain Data Analysis

The future of Brain Informatics will be affected by the ability to do large-scale mining of fMRI and EEG brain activations. The key issues are how to design the psychological and physiological experiments for obtaining various data from human problem solving system, as well as how to analyze and manage such data from multiple aspects for discovering new models of human problem solving system. 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 [4,6,10,11,15]. 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.

A mining process is shown in Figure 1, in which various tools can be cooperatively used in the multi-step process for pre-processing (data cleansing, modeling and transformation), mining and post-processing. Our purpose is to understand activities of human problem solving system by investigating the spatiotemporal features and flow of human problem solving system, based on functional relationships between activated areas of human brain for each given task; More specifically, at the current stage, we want to understand:

- how a peculiar part (one or more areas) of the brain operates in a specific time;
- how the operated part changes along with time;
- how the activated areas work cooperatively to implement a whole problem solving system;
- how the activated areas are linked, indexed, navigated functionally, and what are individual differences in performance.

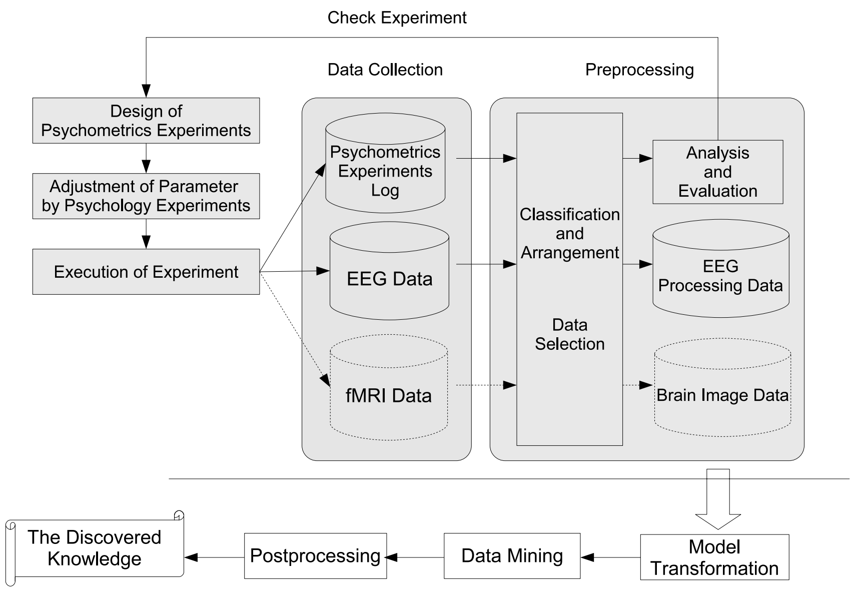


Fig. 1. The mining process

3 The Experiment of an ERP Mental Arithmetic Task with Visual Stimuli

In this work, the ERP (event-related potential) human brain waves are derived by carrying out a mental arithmetic task with visual stimuli, as an example to investigate human problem solving process. ERP is a light, sound, and brain potential produced with respect to the specific phenomenon of spontaneous movement [2]. Since the potential is very weak, the same stimulus can be repeated and given, and furthermore addition average processing can be performed. It argues about ERP in time until a certain wave-like peak appears from a stimulus presentation time called P300. This is called latent time and various knowledge about the mental activity whose measurement is impossible is acquired from outside.

3.1 Outline of Experiments

The experiment conducted this time shows a numerical calculation problem to a subject, and asks the subject to solve it in mental arithmetic, and the shown sum has hit, or it pushes a button, and performs a judging of corrigenda. The form of the numerical calculation to be shown is the addition problem of "augend + addend = sum". The wrong sum occurs at half the probability, and the distribution is not uniform. Figure 2 gives an example of the screen state transition. Type 1 is two digits addition. Type 2 is eight numbers appear, but it is not necessary to calculate. Both of them, the figure does not remain on the screen.

	State 1	State 2	State 3	State 4	State 5	State 6	State 7	State 8
1	1	9	+	2	6	=	4	5
2	6	3	5	8	1	2	7	4

Type 1 : 19+26=45
Type 2 : random number

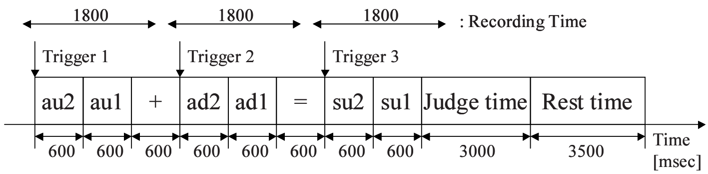
Fig. 2. Example of the screen state transition

3.2 Visual Stimuli

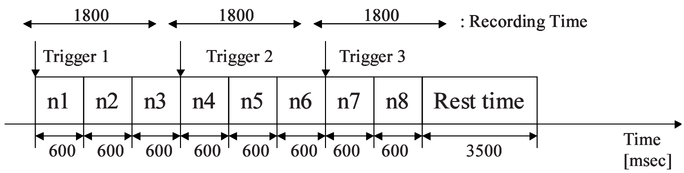
In the experiments, three states (tasks), namely, *visual on-task*, *visual off-task*, and *no-task*, exist by the difference in the stimulus given to a human subject. *Visual on-task* is the state which is calculating by looking a number. *Visual off-task* is the state which is looking the number that appears at random. *No-task* is the relaxed state which does not work at all. We try to compare and analyze how brain waves change along with the different tasks stated above.

3.3 Trigger Signal and Timing Chart

It is necessary to measure EEG relevant to a certain event to the regular timing in measurement of ERP repeatedly. In this research, since the attention was paid to each event of augend, addend, and sum presentation in calculation activities, three trigger signals with respect to these events were set up, respectively. Pre-trigger was set to 200 [msec], and addition between two digits are recorded in 1800 [msec], respectively. Figure 3 gives an example of the time chart for a two-digit addition and off-task. "au" is augend, "ad" is addend, and "su" is sum. "n" is the random number (1-digits). Therefore "au2" is MSD (last 2-digits) of augend, and "au1" is LSD (last 1-digits) of augend.



(a) Trigger timing of Type 1



(b) Trigger timing of Type 2

Fig. 3. Trigger timing

3.4 Experimental Device and Measurement Conditions

Electroencephalographic activity was recorded using a 64 channel BrainAmp amplifier (Brain Products, Munich, Germany) with a 32 electrode cap as shown in Figure 4, which are based on an extended international 10-20 system. The channels with the mark of double circles in Figure 4 will be mainly discussed with their ERP data in this paper. Furthermore, two additional channels, eye movement measurement (2ch) and trigger signal detection (3ch), are also used.

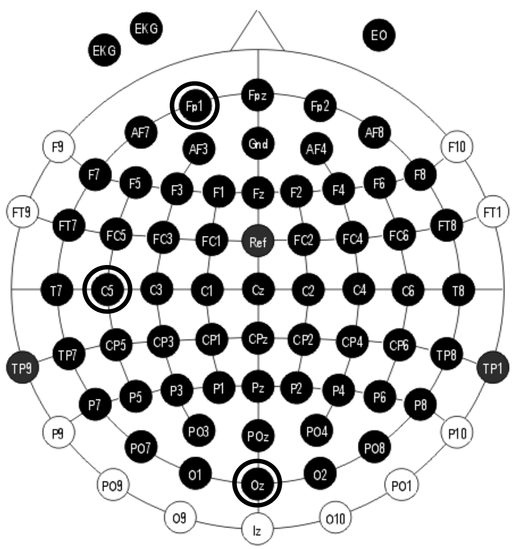


Fig. 4. EEG cap electrode

The electrode adopted for this experiment is the cap electrode and is used as a standard electrode for measuring both earlobes. The sampling frequency is 2500Hz to be processed. The number of experimental subjects is 20.

4 Multi-aspect Data Analysis

4.1 ERP

For the measured EEG data, a maximum of 40 addition average processing were performed, and the ERP was derived by using Brain Vision Analyzer (Brain Products, Munich, Germany). Generally speaking, the Wernicke's area of a left temporal lobe and the prefrontal area are related to the calculation process [5]. In this study, we compare calculation activities and non-calculation activities by focusing on some important channels (Fp1, C5, Oz). We pay attention to recognition of the number, short-term memory and attentiveness, as well as compare ERP of Type 1 and Type 2, and study a problem solving process for a calculation in a macro view.

Figure 5 shows the ERPs in channels Fp1, C5, Oz. First, we discuss the channel Fp1, which is the prefrontal area related with attention. The presence of the calculation activity is closely related to the depth of attention to the number. The activation of Fp1 is earlier than that of the visual area, and it appears remarkably with On-task. Next, we discuss the channel Oz, which is the visual related area with respect to the gaze. We can see that it is activated by a numerical appearance, regardless of the presence of the calculation activity. However, Type 2 shows high positive potential in all almost time. And, it is expected that an appearance of P400 in Oz is related to processing and memory of an afterimage in a brain. Hence, it is necessary to investigate this phenomenon deeply with the temporal change around the visual area. Finally, we discuss the channel C5, which is part of the left temporal lobe with respect to the logical interpretation. Contrary to our expectation, the difference of clear ERP to the presence of the calculation activity was not found. It is guessed that what number appeared without any relation to the calculation is unconsciously confirmed.

Furthermore, we pay attention to the calculated time zone and study response in each part. In this time zone, we can see that the prefrontal area related channels (Fp1, Fp2, AF8, F10) are activated. An interesting point we observed is that the behavior of the left and right brain when calculating is with some individual differences. Let us to analyze this phenomenon from the topography with respect to Trigger 2, as shown in Figure 6. After displayed LSD, the display time zone is from 200 to 320 milliseconds. We can see that the potential distribution of the left and right brain is different between subjects, and subject A used the whole brain thoroughly. We try to understand it in depth by analyzing influence by good of the calculation and not good as well as how to solve problems, from the viewpoint of multi-aspect mining.

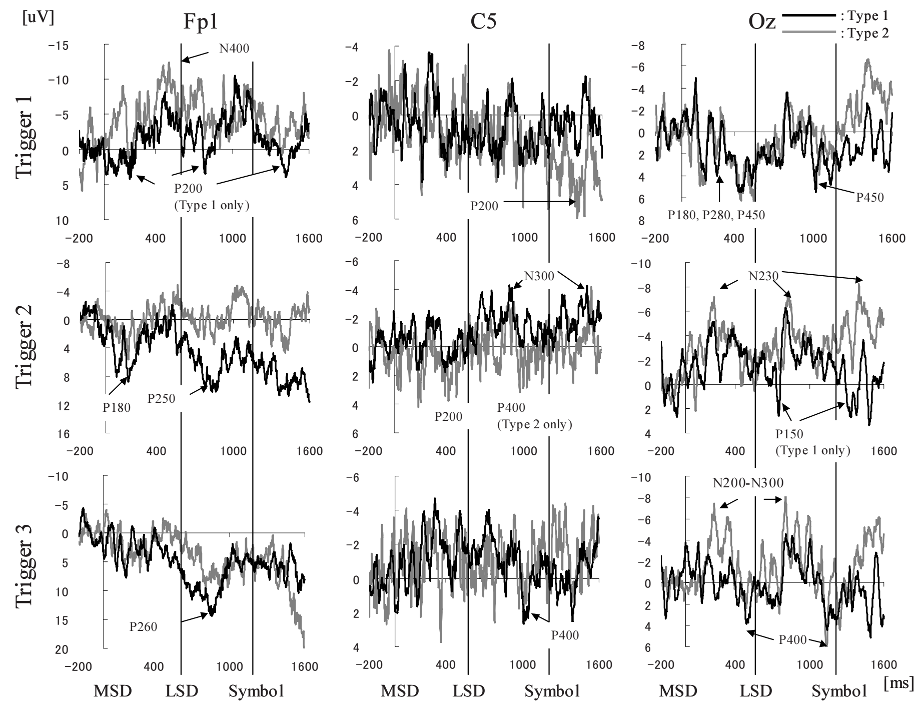


Fig. 5. ERP (Fp1,C5,Oz)

4.2 Peculiarity Oriented Mining

It is clear that ERPs are different for channels over the time. Although detecting the concavity and convexity (P300 etc.) is easy by using the existing tool, it is difficult to find a peculiar one in the multiple channels with the concavity and convexity [7,8]. In order to discover new knowledge of human information processing activities, it is necessary to pay attention to the peculiar channel and time in ERPs for investigating the spatiotemporal features and flow of human information processing system. This subsection introduces our *peculiarity oriented mining (POM)* approach for ERP data analysis.

POM in the Attribute-Value Level. The main task of POM is the identification of peculiar data. An attribute-oriented method, which analyzes data from a new view and is different from traditional statistical methods, is recently proposed by Zhong *et al.* and applied in various real-world problems [14,15].

Peculiar data are a subset of objects in the database and are characterized by two features: (1) very different from other objects in a dataset, and (2) consisting of a relatively low number of objects. The first property is related to the notion of distance or dissimilarity of objects. Intuitively speaking, an object is different from other objects if it is far away from other objects based on certain distance functions. Its attribute values must be different from the values of other objects.

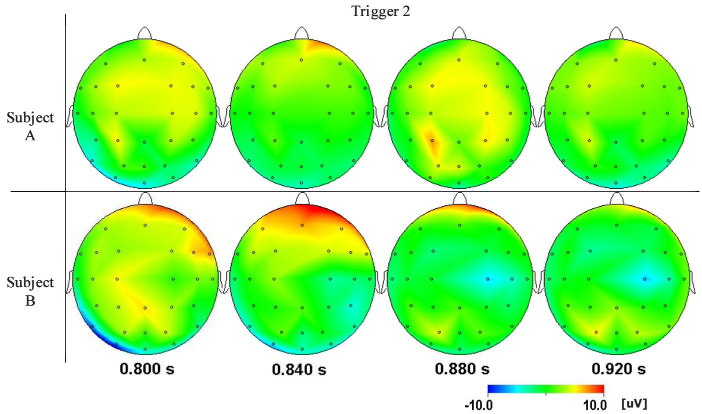


Fig. 6. Topography

One can define distance between objects based on the distance between their values. The second property is related to the notion of support. Peculiar data must have a low support.

At the attribute-value level, the identification of peculiar data can be done by finding attribute values having properties (1) and (2). Let x_{ij} be the value of attribute A_j of the i-th tuple in a relation, and n the number of tuples. Zhong *et al.* [14] suggested that the peculiarity of x_{ij} can be evaluated by a *Peculiarity Factor*, $PF(x_{ij})$,

$$PF(x_{ij}) = \sum_{k=1}^{n} N(x_{ij}, x_{kj})^{\alpha} \tag{1}$$

where N denotes the conceptual distance, α is a parameter to denote the importance of the distance between x_{ij} and x_{kj}, which can be adjusted by a user, and $\alpha = 0.5$ as default.

Based on the peculiarity factor, the selection of peculiar data is simply carried out by using a threshold value. More specifically, an attribute value is peculiar if its peculiarity factor is above minimum peculiarity p, namely, $PF(x_{ij}) \geq p$. The threshold value p may be computed by the distribution of PF as follows:

$$\begin{aligned} threshold = {} & mean\ of\ PF(x_{ij}) + \\ & \beta \times standard\ deviation\ of\ PF(x_{ij}) \end{aligned} \tag{2}$$

where β can be adjusted by a user, and $\beta = 1$ is used as default. The threshold indicates that a data is a peculiar one if its PF value is much larger than the mean of the PF set. In other words, if $PF(x_{ij})$ is over the threshold value, x_{ij} is a peculiar data. By adjusting the parameter β, a user can control and adjust threshold value.

Peculiarity Vector Oriented Mining. Unfortunately, the POM in the attribute-value stated above is not fit for ERP data analysis. The reason is that the useful aspect for ERP data analysis is not amplitude, but the latent time. After smoothing enough by moving average processing, in the time series, we pays the attention to each potential towards N pole or P pole. Furthermore, the channel with the direction different from a lot of channels is considered to be a peculiar channel at that time. Hence, the distance between the attribute-values is expressed at the angle. And this angle can be obtained from the inner product and the norm in the vector. Let inclination of wave i in a certain time t be x_{it}. The extended PF corresponding to ERP can be defined by the following Eq. (3).

$$PF(x_{it}) = \sum_{k=1}^{n} \theta(x_{it}, x_{kt})^{\alpha}. \tag{3}$$

However, θ in Eq. (3) is an angle which the wave in time t makes. For the θ, we can compute for an angle using Eq. (4).

$$cos\theta = \frac{1 + x_{it} \cdot x_{kt}}{\sqrt{1 + x_{it}^2}\sqrt{1 + x_{kt}^2}}. \tag{4}$$

Application of the Extended POM Method. The extended POM method has been used for the ERP data analysis. Figure 7 shows a result in which the peculiarity in ERP data with respect to addition Type 1 (between 2 digits with the visual stimulus Trigger 1) is presented. All channels show high peculiarity from 200ms to 400ms after presented stimuli. The reason is that a wavy ruggedness of ERP changes violently, and it is a remarkable response in the frontal cortex and lobus occipitalis. On the other hand, the PF values of temporal lobes, such as C5, C6 and P6 are high in all time zones. These channels have a unique property of latent time. The higher PF value is related to the interestingness in the ERP data. Hence, it is necessary to investigate this phenomenon deeply with the medical standpoint.

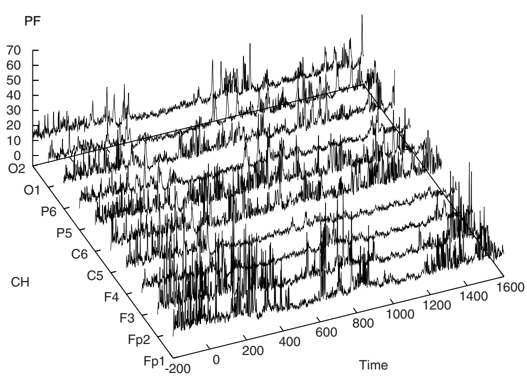


Fig. 7. Peculiarity in ERP data

5 Conclusion

In this paper, we described a more whole process from the design of the ERP experiments of a mental arithmetic task with visual stimuli, carrying out such an experiment to collect the EEG data, to multi-aspect EEG data analysis by using the proposed Peculiarity Vector Oriented Mining method etc. Some preliminary results showed the usefulness of our methodology. By introducing multiple trigger signals, it is possible to analyze human calculation process in detail, as a case study for investigating human problem solving system. The previous design of ERP experiments only gave simple stimulus (e.g., sound stimulus, light stimulus, etc.) and very few of them are with respect to investigating a more whole human problem solving mechanism.

Our future work includes obtaining and analyzing more subject data, combining with fMRI human brain image data for multi-aspect analysis in various approaches of data mining and reasoning.

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