EEG-Based Cortical Localization of Neural Efficiency Related to Mathematical Giftedness

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Abstract. Using two inductive reasoning tasks with high and low levels of complexity, this electroencephalogram (EEG) study examined the relationship between gamma-band response (GBR) of human brain and neural efficiency in math-gifted and average-level adolescents. The event-related synchronization/desynchronization (ERS/ERD) maps of math-gifted subjects and average-level subjects were analyzed in the first place. Furthermore, by means of feature selection based on a sequential forward floating search (SFFS) algorithm, this study investigated the important EEG scalp locations for discriminating cortical areas between groups of subjects and between task conditions. The experimental results show that math-gifted adolescents can more efficiently recruit fronto-parietal cortices while performing both levels of inductive reasoning tasks. Right frontal and bilateral parietal cortices are suggested to be highly involved in neural efficiency related to mathematical giftedness.

Keywords: Neural efficiency, EEG analysis, gamma-band response, fronto-parietal cortices, mathematical giftedness.

1 Introduction

Neural efficiency hypothesis of intelligence suggests that individual difference in cognitive ability can be reflected by efficient recruitment of neural resource of the brain, which derives from the disuse of many brain areas irrelevant to good task performance and more extensive use of specific task-relevant areas [1]. Additionally, long-term training or skilled expertise resulting in reduced working memory load also affects individual's neural efficiency, which is manifested as a decrease of brain activation [2, 3]. Frontal lobe of the brain has typical working memory and cognitive control functions, the activation of which is correlated with monitoring requirement, memory load, or effort of tasks [4]. Therefore, improved working memory performance can result in reduced activation in frontal lobe. In addition, fronto-parietal network, some parts of parietal lobe, precuneus, thalamus, temporal and frontal gyrus have also been suggested to be involved in neural efficiency [1, 5].

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Mathematically gifted adolescents have been found having enhanced functions in prefrontal, frontal, parietal and temporal cortices, and highly adaptive cognitive system for problem solving [5, 6]. However, the accurate brain regions are not explicitly located, where neural resource is "tuned" by individuals with mathematical intelligence or expertise [7]. It has been found that cognitive tasks induce widespread gamma-band response (GBR) in cortical EEG [8]. The increase of GBR (40 Hz) is closely related to attention, decision, high-order cognition, and shows close spatial correspondence with fMRI blood oxygenation level dependent (BOLD) variations in activated brain regions [9]. Meanwhile, the augmented gamma activity is discovered to be modulated by the complexity of cognitive tasks and correlated with working memory load of human brain [10, 11]. Based on the spatial distribution of EEG GBR features, this study aims to determine the cortical localization of neural efficiency on scalp electrodes through a feature (or channel) selection method and two mathematical reasoning tasks, which can maximally represent the discriminating cortical regions of efficient neural activation between math-gifted and average-level adolescents.

2 Materials and Methods

2.1 Subjects

In this study, the math-gifted group included 8 adolescents (5 males and 3 females with mean age 16.5) from the Science and Engineering Experimental Class at Southeast University (Nanjing, China), who had been awarded prizes in nationwide or provincial mathematical competitions. Therefore, they were viewed as proficient in mathematical and logical thinking. The control group was composed of 7 students (5 males and 2 females with mean age 16.3) from the Nanjing Fourth High School, who achieved average-level performance in mathematical tests of the school. Exclusion criteria included left handedness, neurological illness, and history of brain injury. All subjects were given informed consent and the study was approved by the Academic Committee of the Research Center for Learning Science, Southeast University, China.

2.2 Experimental Paradigm

The experiment in this study adopted two numerical inductive reasoning tasks with low to high complexity, similar to those used in [12]. The experimental protocol is shown in Figure 1. In Figure 1a, three numbers in the triangle were associated with a certain calculation rule, such as 'A+B=C' or 'A+C=B', and four numbers in the square were related to a calculation rule with increased complexity, such as 'A+B=C+D' or 'B=A+C+D'. Each trial of a task was constituted by three triangles/squares, which involved two basic processes, i.e., rule induction and rule application, as shown in Figure 1b. The rule induction process at the left of the arrow aimed to find the calculation rule from the first two triangles/squares, and the validity of this calculation rule was verified by the third triangle/square at the right of the arrow, i.e., rule application. The calculation rule only involved '+' and '-'.

Each task session was composed of a valid block and an invalid block. The valid block included 30 trials with congruent calculation rule between rule induction and rule application processes. The invalid block included 30 trials in which the rule in the application process was not congruent with that in the induction process.

The timeline of stimuli presentation is shown in Figure 1c and 1d. The trials in all the blocks of the two tasks were randomly presented. The onset of the stimulus started after presenting a fixation point for 1000ms and a blank screen for 500ms, and the triangles/squares were presented sequentially along the timeline with an interval of 2000ms, as shown in Figure 1c and 1d. Therefore, the rule induction process lasted for 4000ms and the rule application process had no time limit but was controlled by subjects. When the last triangle/square was presented, subjects were asked to judge whether the rules of the two processes were consistent or not as fast and as accurately as possible by pressing “K” for “valid” and “D” for “invalid” on the keyboard.

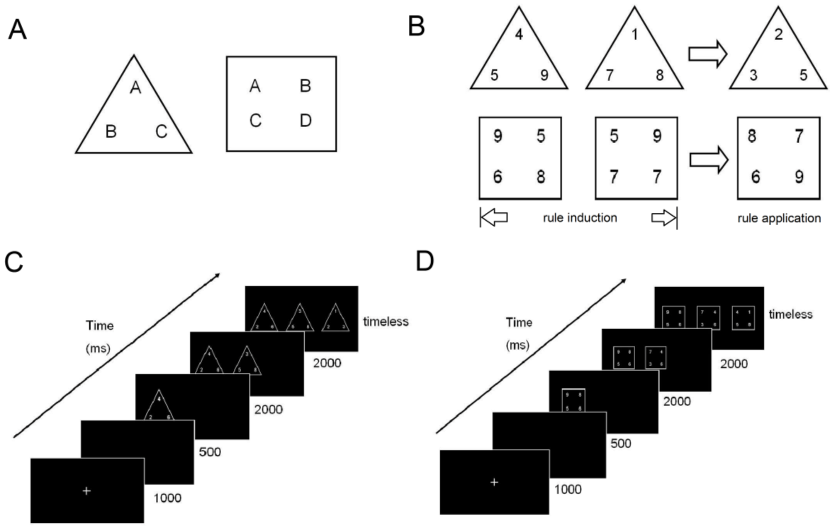

Fig. 1. Experiment protocol: (a) A triangle with three numbers and a square with four numbers; (b) Samples of numerical inductive reasoning tasks with two levels of complexity; (c) Timeline of stimuli presentation of low-complexity task; (d) Timeline of stimuli presentation of high-complexity task

2.3 EEG Recording and Preprocessing

The EEG data were recorded by a 60-channel Neuroscan international 10-20 system with sampling rate 1000 Hz. Reference electrodes were located at the bilateral mastoids of subjects, and electro-oculographic (EOG) signals were simultaneously recorded by four surface electrodes to monitor ocular movements and eye blinks.

The EEG signals were band-pass filtered between 1 Hz and 60 Hz. EEG trials were extracted using a time window of 4500ms, which covers 500ms pre-stimulus period and 4000ms post-stimulus period. After baseline-correction and artifacts rejection, 26 to 43 effective task trials were retained for each subject in each task session.

2.4 Extraction of Gamma Band Power Changes as Features

In the 4000ms period of the rule induction process, feature extraction was conducted from GBR (35-45Hz) in each EEG channel by calculating event-related synchronization/desynchronization (ERS/ERD), which was expressed as the percentage of power increase/decrease in relation to the baseline resting state:

$$ERS\,/\,ERD(f,\Delta t) = [A(f,\Delta t) - R(f)]\,/\,R(f)]\times 100\% \tag{1}$$

where Δt is a time window of 500 ms, $A(f,\Delta t)$ is power spectrum density at frequency f of an EEG signal in time range Δt, and $R(f)$ is power spectrum density at the same frequency in pre-stimulus interval of the signal. Positive value of Eq. (1) represents ERS and negative value is ERD.

By using a sliding window with a step of 25ms, gamma ERS/ERD was calculated for each time window (500ms) at a sample point within a trial. Therefore, each window overlapped the previous one by 475 sample points. The feature extraction of gamma ERS/ERD was conducted for all channels and 60 features in total were thus produced at each sample point within a trial.

2.5 Feature Selection by Sequential Forward Floating Search Algorithm

Inductive reasoning is mediated by the coordination of multiple brain areas, including prefrontal, frontal, parietal, and some subcortical regions, etc. [12, 13]. As an important moderating variable of neural efficiency, different brain areas show different activation dependency on learning, memory, effort, ability, etc. [1]. While confronting with tasks of (subjectively) low to high difficulty, individual cognitive level affects the investment of cortical resource, resulting in differential mental states. For localizing the common cortical regions of subjects that were maximally modulated by reasoning task complexity and logical thinking ability, a sequential forward floating search (SFFS) algorithm was used to conduct electrode-based cortical region detection. SFFS algorithm can obtain optimum combinations of "gamma ERS/ERD" features (and thus channels) by promoting classification accuracy through pairwise discrimination between mental states [14].

Let Y be the feature space composed of D features:

$$Y = \{y_j \mid j = 1,\dots,D\} \tag{2}$$

and X_k are the features selected from Y, which consists of k features with the best discrimination accuracy in the feature space

$$X_k = \{x_j \mid j = 1,\dots,k, x_j \in Y\}, k = 0,1,\dots,D \tag{3}$$

X_k is firstly initialized as an empty set with 0 feature selected, i.e., $X_0 = \phi$, $(k = 0)$. The feature selection procedure is conducted in "growing" and "pruning" phases alternatively. During the growing phase, the best feature x^+ is added to the selected feature subset as follows,

$$X_{k+1} = X_k + x^+ ,\ \ k = k + 1 \tag{4}$$

which makes the feature subset X_{k+1} have the highest discrimination, i.e.,

$$x^+ = \arg\max_{x \in Y - X_k} J(X_k + x) \tag{5}$$

Function J is mean classification accuracy achieved by linear discriminant analysis (LDA) with cross-validation. When $k > 2$, the selection procedure enters into pruning phase after growing in each iteration. During this phase, some features in X_k will be removed in turn. If the removal of x^- in X_k results in better discrimination, i.e.,

$$J(X_k - \{x^-\}) > J(X_k) \tag{6}$$

$$x^- = \arg\max_{x \in X_k} J(X_k - x) \tag{7}$$

then this feature will be deleted from X_k, i.e.,

$$X_{k-1} = X_k - x^- ,\ \ k = k - 1 \tag{8}$$

While k is up to the preset maximum number of selected features (channels), the selection procedure will end. In this study, the maximum number of accepted channels was set to 15. The feature selection based on binary-classification was conducted between subject groups in each task condition, and also conducted between tasks in each group respectively. In all the selected feature combinations, we could find the optimum scalp channel locations with the highest accuracy in discriminating mental operations and subject groups respectively.

3 Results and Discussions

3.1 Augmented Gamma Band Response in Fronto-Parietal Cortices

The increase of gamma power was found to be modulated by task complexity and task performer (math-gifted/average-level). As shown in Figure 2, the high-complexity task induces more gamma ERS in the two groups than the low-complexity task. Meanwhile, the math-gifted group shows different gamma ERS distribution compared with the control group in the two tasks, that is, the math-gifted adolescents recruited more resource in fronto-parietal cortices for complex task but less for simple task. Fronto-parietal cortices are involved in event-related activation of logical reasoning, which are mainly manifested as gamma ERS distributed in frontal, sensorimotor, and parietal cortical regions. Other parts of the brain, such as prefrontal, temporal, occipital cortices also show increased gamma power.

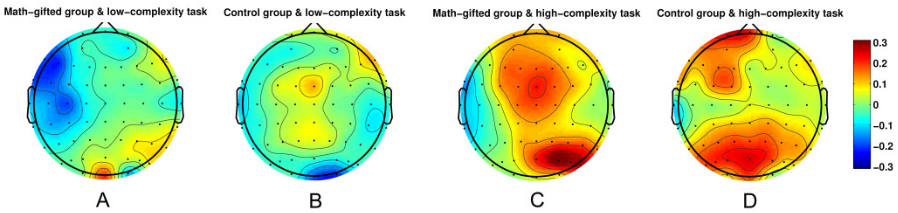

Fig. 2. EEG topological maps of group-averaged gamma ERS/ERD, with positive value representing ERS and negative value ERD: (a) Math-gifted group in low-complexity task; (b) Control group in low-complexity task; (c) Math-gifted group in high-complexity task; (d) Control group in high-complexity task.

3.2 Optimum Channel Combinations for Distinguishing Mental States

In Figure 3a, the math-gifted group shows the highest accuracy of 0.7302 in discriminating high-complexity and low-complexity tasks. Their brain regions that were maximally modulated by task complexity were located at frontal (F1 and F3), parietal-occipital (P2 and PO4) and sensorimotor (C1, C3, C4 and C6) cortices. Left-lateral frontal regions are responsive to implicit relation synthesis of numbers, right-lateral parietal regions are related to internal manipulation of numerical quantity, and occipital cortex reflects visual working memory and visual attention. It is notable that most selected electrodes are in sensorimotor regions, which could be attributed to efficient utilization of fronto-parietal network by math-gifted subjects. Gamma synchronized network plays the role of functional binding between posterior parietal cortex and frontal regions to complete numerical information processing. The increased gamma synchronization can be reflected by increased gamma power [8].

In the control group, only 5 electrodes were selected with the highest accuracy of 0.6707 in discriminating two tasks, which are FP1, POZ, PO6, PO8 and OZ, as shown in Figure 3b. These sites of scalp electrodes indicate that left-lateral prefrontal cortex and parieto-occipital cortices are the most significant brain regions affected by task complexity in average-level subjects. As prefrontal activity reflects attention and cognitive control and parieto-occipital cortices are related to visual response, task complexity change does not significantly affect gamma activity change within fronto-parietal cortical area in average-level subjects.

During the high-complexity task, except for electrodes PO7, OZ and O2 related to visual response, the channel combination with the highest accuracy of 0.6699 in discriminating the two groups focuses on right frontal-centroparietal regions (F2, FCZ, FC4, CZ and CP1), as shown in Figure 3c. Notably, math-gifted subjects show extensive gamma ERS in frontal cortex, especially enhanced right-lateral frontal cortex, as shown in Figure 2. During numerical inductive reasoning, the right frontal regions conduct spatial information processing involved in arithmetic rules and are adequately utilized by math-gifted subjects.

By comparison, a higher accuracy of 0.7106 in discriminating the two groups was found in the low-complexity reasoning task. The topological map of channel combination sketches a characteristic of fronto-parietal distribution, as shown in Figure 3d, involving right frontal, right sensorimotor, and bilateral parietal regions (F6, FC2, C6, CP1, CP4, P3 and P4), which indicates that a coherent fronto-parietal cortical network might be involved in efficient operation by math-gifted subjects.

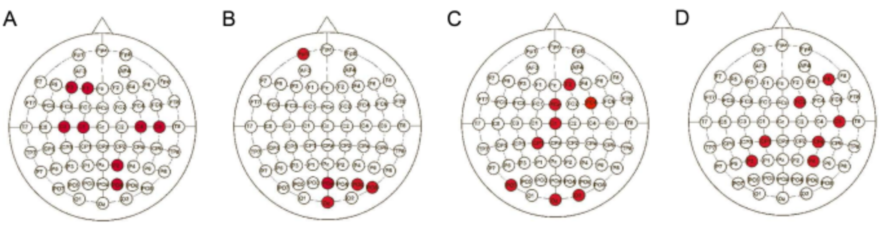

Fig. 3. Topological maps of optimal channel combinations based on SFFS: (a) Channel combination of math-gifted group between tasks; (b) Channel combination of control group between tasks; (c) Channel combination of high-complexity task between groups; (d) Channel combination of low-complexity task between groups.

4 Conclusions

This study shows that between math-gifted and control subjects, right-lateral frontal and bilateral parietal cortices represent the highly discriminating cortical areas where neural resource is effectively recruited by math-gifted adolescents to adapt to different internal requirement for cognitive processing. Specially, right frontal lobe was selected in both of the tasks through high utilization in the complex task and economical usage in the simple task by math-gifted subjects. The activation of right frontal lobe can be viewed as an optimum indicator of neural efficiency. The selected scalp locations coincide well with the important neural mechanism of math-gifted adolescents, i.e., highly developed right frontal lobe and bilateral fronto-parietal network [6, 15].

The results from this study are meaningful for mathematical learning of children and adolescents. Their neurodevelopment has adjustable characteristics based on neuroplasticity, especially for children and early adolescents whose frontal lobe still lies in a developing stage, e.g., laterality of frontal cortical activity can be modulated by on-line neurofeedback to improve individual's neural response.

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