Attention quantification based on steady-state somatosensory evoked potentials

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Abstract This paper describes a newly developed quantitative measurement method of “attention” based on steady-state somatosensory evoked potentials (SSSEPs). To demonstrate the feasibility of the method, we carried out a task that subjects attend on the right or left index finger both of which frequency-tagged mechanical vibration stimuli were presented. In the task, the subjects are also instructed to count the number of pulsed mechanical stimuli given to the middle finger of the attended hand. After applying a narrow band pass filter, principal component analysis (PCA) was used to extract principal components (PCs). Subsequently, time courses of powers of reconstructed PC scores were analyzed in each subject, it was found that powers of SSSEPs in attended conditions were larger than those of non-attended conditions.

Key words attention, steady-state sensory stimuli, steady-state somatosensory evoked potential (SSSEPs)

1. Introduction

“Attention” is one of the important brain information and well studied in the fields of not only cognitive sciences but brain-computer interfaces (BCIs) [1]. Recently, increases of sensory evoked potentials during attention have been reported [2]–[5]. Although there are some attempts to measure brain activities reflecting attention quantitatively, no generally used method is established. Realization of quantitative measurements of attention would contribute to clarify cognitive functions. Furthermore, they may also contribute for accuracy improvement of BCIs and development of diagnostics supporting techniques of attentional disturbance [6].

In this study, we proposed a novel quantitative measurement method of “attention” based on frequency-tagged steady-state somatosensory evoked potentials (SSSEPs) combining with principal component analysis (PCA) and wavelet analysis. The SSSEPs were elicited by mechanical vibrations presented to the right and left index fingers. The proposed method was evaluated by the small number of electroencephalogram (EEG) data sets obtained for the mechanical vibrations with some tagged frequencies.

2. Materials and Methods

2.1 Participants

Four healthy right-handed male adults (s1–s4) gave informed consent and participated in the EEG experiments.

2.2 Data acquisition

EEGs were recorded from 128 electrode locations covering the entire head by using 256-ch digital EEG system (BioSemi, Inc.). The 128 locations were shown in Fig. 1. The EEGs were sampled 512 Hz. Subjects were seated in a comfortable armchair, and were asked to place their index fingers on the tactile stimulation device (DC solenoid: the pressure power, 0.5 N). The mechanical vibration frequency f presented to one index finger was one of f = \{5, 7, 13, 15, 17, 20, 25\} Hz, whereas f0 to another index finger was 45 Hz. At the same moment, the pulse stimuli (random-
Next, PCA was applied to the referenced EEGs to extract their principal components (PCs) and reconstruct their scores (PC scores) as well. In general, PCA is a multivariate analysis to identify dominant features in multichannel-recorded data, and express the data by small numbers of principal components. When $V_N(t)$ are EEGs with $N$ channels, the PC scores $M_N^{(p)}(t)$ was given by the following equation using an eigenvector $w_N^{(p)}$ of $p$th main component ($p = 1, ..., P$).

$$M_N^{(p)}(t) = V_N(t)w_N^{(p)}$$  \hspace{1cm} (1)

The first principal component (PC1) accounts for most of the variability in the data, while each of the succeeding components in turn account for the highest amount of the remaining variability. In this study, PCA transformed a connected data set, $[V_{n_{f_{\text{att}}}}^{(1)}(t), V_{n_{f_{\text{att}}}}^{(2)}(t), ..., V_{n_{f_{\text{non}}}}^{(K)}(t), V_{n_{f_{\text{att}}}}^{(1)}(t), V_{n_{f_{\text{non}}}}^{(2)}(t), ..., V_{n_{f_{\text{non}}}}^{(K)}(t)]$ (t = 500 ~ 3500 ms), into a set of principal components and produced a set of eigenvectors, $w_{n_{f_{\text{att}}}}^{(1)}, ..., w_{n_{f_{\text{non}}}}^{(K)}$ which had a common spatial patterns among all epochs. Then, it would appear that PC1 and second principal component (PC2) reflected SSSEPs, so that PC1 and PC2 were employed in this study. Moreover, $p$th PC scores at $k$ epoch, $M_{n_{f_{\text{con}}}}^{(k,p)}(t)$, were obtained by projecting the EEGs $V_{n_{f_{\text{con}}}}^{(k)}(t)$ on the space spanned by the eigenvectors $w_{n_{f_{\text{con}}}}^{(p)}$ (eq.(1)). These processes enabled to detect eigenvectors of frequency-tagged SSSEPs represented as scalp topographies, and we can analyze amplitude of the SSSEPs at a single trial based on the eigenvectors. This idea followed by a previous study [6] showing that SSSEP scalp voltage topography and cortical sources were not different between attended and unattended hand.

Subsequently, wavelet analysis was applied to the PC1 scores, $M_{n_{f_{\text{con}}}}^{(k,1)}(t)$, and PC2 scores, $M_{n_{f_{\text{con}}}}^{(k,2)}(t)$, to obtain the sum of spectrograms (time-frequency powers) of both PC1 and PC2 scores for “att” and “non-att” conditions at each frequency $f$ as follows.

$$E_{n_{f_{\text{con}}}}^{(k,1:2)}(t,f) = \sum_{i=1}^{2} |\Psi(t,f)M_{n_{f_{\text{con}}}}^{(k,i)}(t)|^2$$  \hspace{1cm} (2)
Where $\Psi(t, f)$ is the Morlet mother wavelet function. The time-frequency powers were averaged among all trials for each condition, and the each averaged power is $E_{n/fatt}^{(X_k, 1, 1)}(t, f)$ and $E_{n/fnon}^{(X_k, 1, 1)}(t, f)$. Finally, the averaged powers of "att" and "non-att" conditions were normalized by use of both means and standard deviations of averaged power in the "non-att" condition as follows.

$$E_{n/fatt}^{(X_k, 1, 2)}(t, f) = \frac{E_{n/fatt}^{(X_k, 1, 2)}(t, f) - E_{n/fnon}^{(X_k, 1, 2)}(t, f)}{\text{sd}(E_{n/fnon}^{(X_k, 1, 1)}(t, f))}$$

$$E_{n/fnon}^{(X_k, 1, 2)}(t, f) = \frac{E_{n/fnon}^{(X_k, 1, 2)}(t, f) - E_{n/fnon}^{(X_k, 1, 1)}(t, f)}{\text{sd}(E_{n/fnon}^{(X_k, 1, 1)}(t, f))}$$

Where sd( ) and | represented standard deviation at time dimension and time-average, respectively. When values $E_{n/fatt}^{(X_k, 1, 2)}(t, f)$ and $E_{n/fnon}^{(X_k, 1, 2)}(t, f)$ are larger than 3 (i.e., "3 SD"), that is, more than three times the standard deviation of the sd($E_{n/fnon}^{(X_k, 1, 2)}(t, f)$), it was assumed that the values include significant modulation of power relative to "non-att" condition. "3 SD" corresponded to significant levels of $p < 0.01$. Then, the time lengths of significant modulation at "att" condition were compared with those of "non-att" condition.

3. Results and Discussion

3.1 PCA analysis

Figs. 4 (a) and (b) showed the eigenvector topographies of PC1 and PC2 on the scalp in subject 1 obtained by PCA. "L" and "R" in Fig. 4 indicated the "left" and "right" index fingers stimulated by frequency-tagged ($f = \{5, 7, 13, 15, 17, 20, 25\}$ Hz) stimulation. The percentages shown under the topographies were proportions of PC1 or PC2. Topographies of PC1 and PC2 showed common distributions among all frequencies. Note that the positive and negative signs of the eigenvector topography had no meaning. Most of the topographies of PC1 showed posterior-anterior polarity distribution, while most of the topographies of PC2 showed the polarity between bilateral temporal regions in all subjects. Mean proportion of PC1 and PC2 over all frequencies and subjects were 38.1 ± 4.0 % and 25.2 ± 4.0 %, respectively. On the other hand, eigenvector topographies of PC3 did not show a common pattern among frequencies. Mean proportion of the PC3 over all frequencies and subjects was 9.0 ± 2.1 %. Then, it would appear that PC1 and PC2 mainly reflected SSSEPs, whereas PC3 reflected little. Therefore, PC1 and PC2 were employed in the analysis.

Giabiccioni et al. [2] showed the SSSEPs reflecting activation in bilateral primary somatosensory cortex (SI) when vibrating stimuli were presented simultaneously for several seconds to the left and right index fingers. Meanwhile, Schubert et al. [3] used pseudorandom consecutive but not simultaneously stimuli to both index fingers. They showed bilateral activations in SI and secondary somatosensory cortex (SII) related to P50, N80, P100 which were components of SEP [3]. In addition, the scalp topographies of P50 components for ambilateral stimuli and P100 components for left stimuli showed posterior-anterior polarity distribution, and those of N80 components for ambilateral stimuli showed ipsilateral-contralateral polarity distribution [3]. Hence, the posterior-anterior polarity distributions of the topographies of PC1 suggested a bilateral parietal generator of SSSEPs in SI and the one temporal-the other temporal polarity distributions of those of PC2 indicated N80 components.
Figs. 5 (a) showed representative time-frequency powers of PC scores, $E_{n, att}^{(2:1)}(t, f)$ and $E_{n, f,non}^{(2:1)}(t, f)$, in all subjects; s1: attention to 5 Hz-tagged stimuli to the right index finger (5 Hz/Right), s2: 5 Hz/Right, s3: 25 Hz/Right, s4: 13 Hz/Right. Figs. 5 (b) showed percentages of the time lengths that $E_{n, att}^{(2:1)}(t, f)$ and $E_{n, f,non}^{(2:1)}(t, f)$ exceeded +1 (i.e. “1 SD”) showed in x-axis (white and black bars indicate “att” and “non-att” condition, respectively). Figs. 5 (b) indicated that the powers in “att” conditions exceeded “3 SD” while those in “non-att” conditions were even smaller than “2 SD” in all subjects. Here, “2 SD” corresponded to significant levels of p < 0.05.

In this study, PCA was employed to extract SSSEPs modulation by attention. However PCA might not be able to extract SSSEPs from EEGs including mu or beta activity synchronized with SSSEPs. Then, not the analysis using scalp potentials but source estimations by integrative analysis with other modalities such as, functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), would extract SSEPs modulation more exactly.

### 3.2 Wavelet analysis

Percentages of the time length that the normalized time-frequency powers of PC scores, $E_{n, att}^{(2:1)}(t, f)$ and $E_{n, f,non}^{(2:1)}(t, f)$, exceeded “3 SD” at all frequencies and subjects were listed in Table 1. Although there were individual differences, almost all the powers of PC scores in “att” conditions were larger than those in “non-att” conditions at specific tagged frequencies except for s3 (15 Hz/R). In addition, the powers of PC scores in “non-att” conditions were smaller than “3 SD” at any specific tagged frequencies except for s3 (15 Hz/R).

Some previous studies indicated that ERD (event-related desynchronization) occurred at the mu (8–13 Hz) [4], [5] and beta (15–25 Hz) [4], [5] bands during stimulation of the right index finger consecutively. Furthermore, beta band activity decreased during attention to the consecutive stimuli to the right index finger [4]. Mu and beta bands included most frequencies of the stimuli except for 5 and 7 Hz in this experiment. Therefore, the percentages more than 20% at 5 Hz/R in three subjects (s1–s3) might be affected by that 5 Hz was not included in those bands. In addition, this analysis could not detect the significant increases at 20 Hz bands during “att” condition, which observed in previous studies [2], [3], in all subjects. The incongruent results might arise from the difference of the method used in the present study and previous studies [2], [3].

### 4. Conclusion

To extract SSSEPs and measure “attention” quantitatively, we proposed a method based on PCA and wavelet analysis. It was found that proposed method could identify “attention” as modulated amplitudes of SSSEPs elicited by frequency-tagged vibrotactile stimuli simultaneously given to the right and left index fingers. In addition, results suggested that it was effective to select optimal frequency in each subject beforehand, and use the optimal frequency-tagged somatosensory stimulus to detect attention. These results demonstrated the feasibility of the proposed method as not only a novel objective tool of attentional disturbance test but also decoding technique for BCIs.

### REFERENCES


