ABSTRACT

Objective: This study aims to investigate a relationship between a neural correlate of mental workload and the performance of the N-back memory task. Background: Many studies have explored neuronal correlates of mental workload by measuring the brain signal. In particular, the power of the theta rhythm (4-8 Hz) embedded in electroencephalogram (EEG) over the frontal region of the human brain has been shown to vary with mental workload. Studies have shown correlations between the frontal theta power and mental workload via various mental tasks, including the N-back task, Sternberg’s task, the multi-attribute task battery, mental arithmetic tasks and driving tasks, to name a few. However, behavioral evidence regarding the correlation between frontal theta power in individuals and their behavioral mental task performances still remains unclear.

Method: Ten healthy subjects performed the N-back task with various task difficulties (0-3 back tasks), while their EEG signals were recorded using a 20-channel system. The power spectrum of the theta band (4-8 Hz) from bandpass-filtered EEG signals at the frontal channel (Fz) was calculated for each task.

Results: The frontal theta power exhibited significant positive linear correlations with the error rates both in the 2-back and 3-back tasks ($r > 0.68$, F-test, $p < 0.05$), but neither in the 0-back task nor in the 1-back task.

Conclusion: Individuals with poor N-back task performance showed greater frontal theta power, reflecting heavier mental workloads than those with good performance. The results indicate that one may use the frontal theta power of EEG to index individuals’ mental capacity in performing a given task.

Keywords: Mental workload, EEG, Theta rhythm, N-back task

1. Introduction

Traditionally, brain-computer interfaces (BCIs) were considered as systems that enable control of a device via consciously generated brain signals. Such systems range from P300 based spellers, SSVEP based applications, to motor imagery based device control, and so forth [1-2]. More recently, however, a new trend in the field of BCI known as user state monitoring has risen. Utilizing rather passive brain signals – no user intention involved whatsoever – current state of the user can be monitored in real-time [3-4]. Information such as emotional state, attention level, or mental workload are expected to bring benefits not only for the disabled but will also be useful for healthy individuals and even in various industries [1, 3].

Mental workload is one of the most important factors that impacts one’s task performance. An unmanned aerial vehicle simulation revealed that operator’s performance improves when the task was alleviated during high workload situation indicated by a combination of several psychophysiological measurements [5]. Various studies have reported correlations between workload or memory load and power in particular frequency band of electroencephalogram (EEG) signals. Though both alpha (8-12 Hz) and theta (4-8 Hz) band power level are known to be associated with workload level [6], here we focus on theta band since alpha power is reportedly linked to an idling or default mode brain activity [7] and
hence can be regarded as a rather indirect measure of workload.

First introduced by Wayne Kirchner in 1958 [8], N-back task is a continuous performance task that is commonly used as an assessment tool in cognitive neuroscience to measure a part of working memory [9]. The subject is presented with a sequence of stimuli, a single alphabetical letter in most cases, and has to determine whether each letter is the same as the one presented N letters before it. By increasing the N, the subject is required to memorize longer sequence of letters in a rapid pace. It is also a wide-spread tool to manipulate workload in neuroimaging studies [10].

In this study, we analyze EEG signals recorded during N-back task and examine band powers. We test the hypothesis that the amount of change in theta band power is positively correlated to subjects’ task performances represented with error rate, due to heavier mental workloads for worse performers.

2. Methods

2.1. Participants and Data Acquisition

A total of ten healthy subjects (8 males, mean age = 26.7, SD = 6.31, range 19-40) participated in this study signed an informed consent form prior to the experiment. This study was performed in accordance with ethical guidelines and was approved by the institutional review board of Korea University (KU-IRB-12-45-A-2).

20-channel EEG signals were recorded using actiCAP active electrode system in combination with actiCHamp amplifier (Brain Products GmbH, Germany) at 500Hz sampling frequency.

2.2. Stimulus Design

N-back task was presented on a 24-inch 1920 by 1080 resolution monitor by E-Prime script. Behavioral data such as response for each letter and response time were monitored and saved as a worksheet format document.

Each letter was visible for 500ms, followed by a 2 second rest before the next letter (See Figure 1.). Subjects were given a time window of 2.5 seconds for response which equates to time between the instance the letter was presented and the next letter is presented.

2.3. Experimental Paradigm

Each trial of N-back task contained 48 letter stimuli and was repeated twice per task type: 0, 1, 2, 3-back task. The result is 96 letter presentation for each task type. Subjects were given a one-minute rest between every two-minute trial during which they were requested to avoid any movements.

2.4. Behavioral Data Analysis

Response data were categorized into a confusion matrix. Out of four categories – true positive, true negative, false negative, false positive – two false categories were marked as miss and false alarm respectively. Error rate was calculated as a ratio of false responses to total number of letters presented, in this case, 96 letters for each task.

2.5. EEG Data Processing

Acquired EEG signals were initially bandpass-filtered between 2Hz and 60 Hz interval in order to remove both DC component and high-frequency noise. Data from each task were divided into 96 epochs which consists of EEG between -0.5 to 2 seconds from each letter onset. Short-time Fourier transform of 500ms window and 100ms overlap was performed and the power change after onset was averaged over all epochs.

Linear regression between frontal theta power change and task accuracy revealed the relationship. Additionally, parietal beta power was analyzed.
3. Results

3.1. Behavioral Data Analysis

Behavioral data analysis revealed 0.10%, 1.35%, 4.90%, 17.92% error rate averaged over all subjects in 0, 1, 2, 3-back tasks respectively. This confirms that task difficulty increases as $N$ of the task increases. Specific results can be found in Table 1.

Table 1. Error rate for each subject & task type

<table>
<thead>
<tr>
<th>ID</th>
<th>Task Type</th>
<th>0-back</th>
<th>1-back</th>
<th>2-back</th>
<th>3-back</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub01</td>
<td>0-back</td>
<td>0</td>
<td>0</td>
<td>2.08</td>
<td>12.50</td>
</tr>
<tr>
<td>Sub02</td>
<td>0-back</td>
<td>0</td>
<td>2.08</td>
<td>3.13</td>
<td>16.67</td>
</tr>
<tr>
<td>Sub03</td>
<td>0-back</td>
<td>0</td>
<td>4.17</td>
<td>1.04</td>
<td>9.38</td>
</tr>
<tr>
<td>Sub04</td>
<td>0-back</td>
<td>0</td>
<td>2.08</td>
<td>4.17</td>
<td>14.58</td>
</tr>
<tr>
<td>Sub05</td>
<td>0-back</td>
<td>0</td>
<td>1.04</td>
<td>13.54</td>
<td>31.25</td>
</tr>
<tr>
<td>Sub06</td>
<td>0-back</td>
<td>1.04</td>
<td>2.08</td>
<td>3.13</td>
<td>18.75</td>
</tr>
<tr>
<td>Sub07</td>
<td>0-back</td>
<td>0</td>
<td>0</td>
<td>1.04</td>
<td>6.25</td>
</tr>
<tr>
<td>Sub08</td>
<td>0-back</td>
<td>0</td>
<td>3.13</td>
<td>18.75</td>
<td>30.21</td>
</tr>
<tr>
<td>Sub09</td>
<td>0-back</td>
<td>0</td>
<td>0</td>
<td>3.13</td>
<td>26.04</td>
</tr>
<tr>
<td>Sub10</td>
<td>0-back</td>
<td>0</td>
<td>0</td>
<td>1.04</td>
<td>14.58</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>0.10</td>
<td>1.35</td>
<td>4.90</td>
<td>17.92</td>
</tr>
</tbody>
</table>

3.2. Spectral Analysis

Time-frequency analysis confirmed reinforced ERD/ERS activities as task difficulty increased. Though specific features for classification differed depending on each subject’s characteristics, we noticed two frequency bands that exhibited dominance in feature space across most subjects: frontal theta and parietal beta (16.5-20 Hz, “Beta 2”) as Figure 2 demonstrates.

3.3. Performance versus Band Power

The relationship between task performance and band power was examined via linear regression analysis. While results from 0-back and 1-back tasks were unreliable mostly due to error rates close to zero, both 2-back and 3-back tasks exhibited significant positive linear correlations (See Figure 3, 4): for frontal theta and parietal beta respectively, $r = 0.746$, $p = 0.013$ and $r = 0.626$, $p = 0.053$ for 2-back task, $r = 0.679$, $p = 0.031$ and $r = 0.724$, $p = 0.018$ for 3-back task.

4. Conclusion

We conducted an experiment where EEG was recorded from subjects performing N-back tasks of various difficulties. Our original hypothesis was that frontal theta band power,
known to be one of the most dominant spectral features for mental workload, would be higher for worse performing participants due to heavier mental strain compared to better performers.

The results supported our hypothesis by yielding positive correlation with statistical significance. Additionally, parietal beta band power was also revealed as a correlated component. Though we still do not have a very clear answer to its meaning, we can assume it as a plausible result since beta power has been known to be associated with normal waking consciousness and often referred to as the “busy waves” of the brain.

Our results indicate that frontal theta power of EEG can play a vital role in indexing individuals’ mental capacity during a given task. And furthermore, it presents a possibility that some other bands can also reflect mental workload with a comparable reliability.

Acknowledgements

This work was supported by Samsung Electronics Co. Ltd. Additionally, S.P. Kim was supported by the Brain Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ITC & Future Planning (NRF-2006-2005112) and Components & Materials Technology Development Program (10043826) funded by Ministry of Trade, Industry & Energy.

References


Author listings

Jinsoo Jason Kim: homoxmachina@korea.ac.kr
Highest degree: BS, Department of Electrical Engineering, Korea University
Position title: MS Candidate, Department of Brain and Cognitive Engineering, Korea University (Research Assistant, Brain-Computer Interface Laboratory, School of Design and Human Engineering, UNIST)
Areas of interest: BCI, HCI, BCI-based Ergonomics

Miyoung Kim: mykim2002@samsung.com
Highest degree: MS, Computer Science, Kyungpook National University
Position title: Senior Engineer, DMC R&D Center, Samsung Electronics, Suwon, Korea
Areas of interest: Audio Compression, Affective BCI

Eunmi Oh: sait@samsung.com
Highest degree: PhD, Psychology, University of Wisconsin-Madison
Position title: Master (Research VP), DMC R&D Center, Samsung Electronics, Suwon, Korea
Areas of interest: Audio Coding & Processing, Psychoacoustics, Auditory BCI, Perceptual & Cognitive Modeling

Sung-Phil Kim: ksungphil@gmail.com
Highest degree: PhD, Department of Electrical and Computer Engineering, University of Florida
Position title: Professor, School of Design and Human Engineering, UNIST
Areas of interest: BCI, EEG Signal Processing, Neuronal Ensemble Decoding, Statistical Signal Processing