Using a brain-computer interface to compare student electroencephalography data during idleness versus mental math calculation

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Introduction

Brain-computer interface (BCI) technology has recently become a popular research area in biomedical engineering, and its advancement has given rise to accurate assessment of human cognitive states as well as new neurorehabilitation treatments [1].
Electroencephalography (EEG) is a relatively cheap, noninvasive electrophysiological monitoring method used to record brain electrical activity through placing electrodes onto a person's scalp [2]. The invention of commercial EEG headsets adds appeal to EEG-based BCI because they are more portable and convenient to implement. Though these products have not reached the same level of accuracy as more expensive medical grade devices, the quality of commercial EEG technology still offers potential applications for research in classrooms and other real-world settings.
EEG data can be analyzed through the computation of the power spectral densities (PSD) within five defined frequency bands distributed across the scalp [2]. Past experiments have shown that the power values of these frequency bands as EEG indices can provide measures including engagement, mental workload, stress, memory formation, and relaxation [3-5].

Objective

The purpose of this study was to distinguish EEG indices of students during periods of rest, or idleness, versus periods of active mental math calculation in a classroom setting.

Materials

Experiment Apparatus
The BCI platform was composed of a wireless EEG headset and a computer with dual monitors, which contained data acquisition and analysis software. To more easily administer the experiment protocol, a graphical user interface (GUI) was developed using the open-source application PsychoPy [6].

Participants
EEG signals were collected from 15 healthy participants (including the researcher), all of whom were enrolled in high school or a level of higher education. Ages ranged from 16 to 24 years old. The experiment protocol was approved by the Institutional Review Board at the University of Tennessee, Knoxville. All participants gave written informed consent.

EEG Headset
A wireless EEG headset was positioned on each participant's head, allowing EEG signals to be recorded and transmitted to the computer via Bluetooth. The headset used during this experiment was the Emotiv EPOC [7]. The device consisted of 14 electrodes (**Fig. 1**). The sampling frequency was fixed at 128 Hz, and the bandwidth was set at 0.2 to 43 Hz.

Experiment Procedure
Each participant was asked to sit directly facing a computer monitor with both feet flat on the ground and arms positioned comfortably around a keyboard. In preparation for the presentation of stimuli, each participant was instructed to focus on the monitor. S/he was also asked to limit any excessive body motion as well as to maintain normal eye movements and breathing. The total time for the experiment was about 20 minutes per participant (**Fig. 2**).

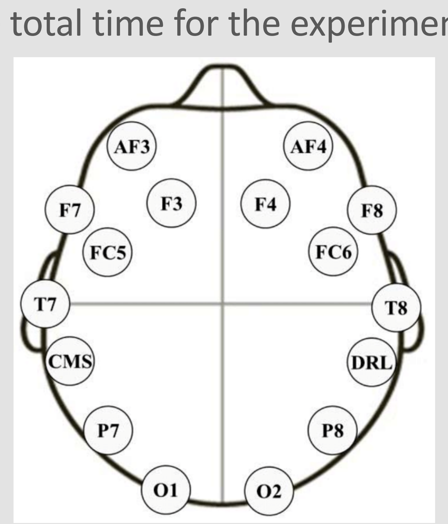

Figure 1
Electrode positioning for the Emotiv EPOC 14-channel headset [7].

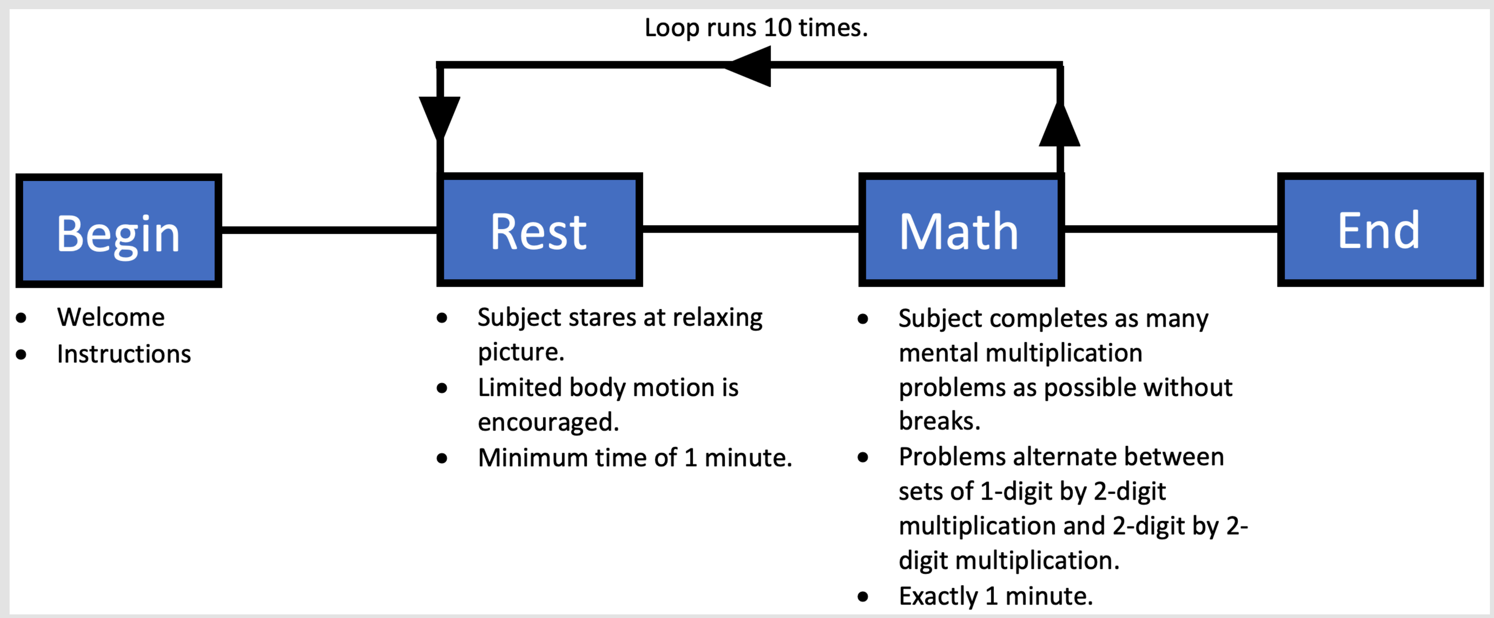

Figure 2
Diagram of experiment protocol.

Methodology

Signal Pre-processing
The MATLAB EEGLAB toolbox was used to process all EEG data [8]. Each EEG recording was applied a digital band-pass finite impulse response (FIR) filter with a low cut-off frequency of 1 Hz and high cut-off frequency of 43 Hz. This filter was also applied in conjunction with Independent Component Analysis (ICA) algorithm to remove any unwanted frequency bands caused by muscular and facial movement artifacts. Artifact subspace reconstruction (ASR) was then used to correct the continuous data.

Frequency Features Extraction
Welch's method and a fast Fourier transform (FFT) were used to calculate the power spectral density (PSD) of five frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-32 Hz), and gamma (33-43 Hz). For the data from each subject, the average powers for the 5 frequency bands during idleness and mental math were determined for each of the 14 channels.

Statistical Analysis
The data were analyzed using sign tests with significance level set at $p = 0.05$.

Results

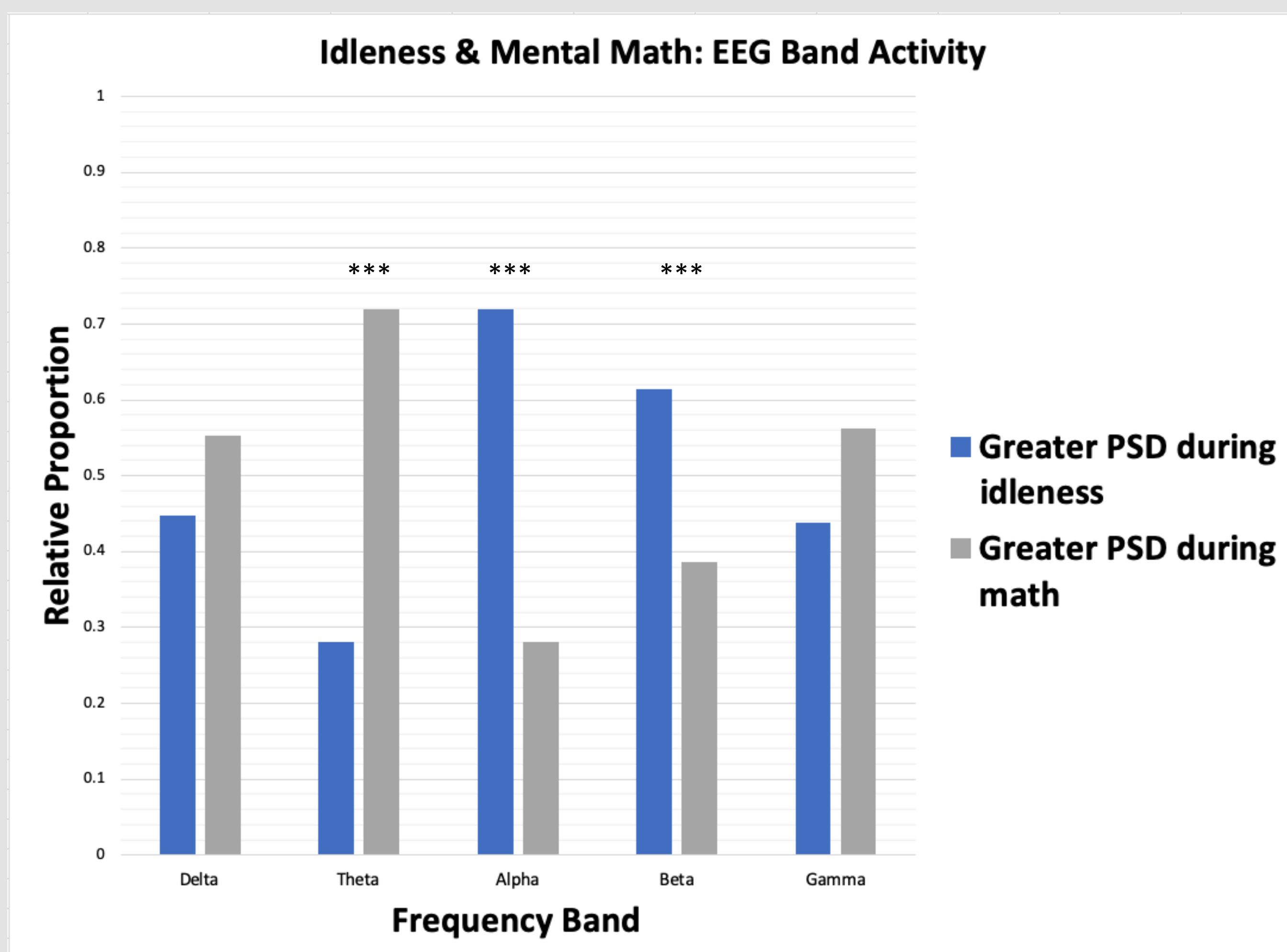

Figure 3
Results of sign tests comparing PSD of each frequency band during idleness and math calculation (*** indicates $p < 0.05$).

Among the 15 subjects with 14 channels each, there showed to be a significant increase in theta activity during mental math ($p < 0.05$).
On the other hand, there showed to be a significant increase in alpha activity ($p < 0.05$) and beta activity ($p < 0.05$) during idleness.
There were no significant differences in either delta or gamma activity between the two conditions.

Conclusion

The results indicate that there is significant difference in theta, alpha, and beta activity between when a subject is inactive and when a subject is actively performing mental math calculation. This conclusion is consistent with past studies that show these three frequency bands to be easily affected by changes in mental effort.
In alignment with the results of this study, other works have shown theta activity to increase with augmented task difficulty and working memory load [9-10]. Oppositely, alpha activity has shown to decrease under the same conditions, leading the increased signal to often be associated with relaxation [9-11].
Increased beta activity, on the other hand, is typically linked to concentration and alertness, which conflicts with the results from this experiment [2]. Although subjects were assumed to be more engaged during mental math calculation, our data suggested that beta activity increased during the idle periods. Upon further literature review, it was found that increased beta signals are also connected to voluntarily suppressed body movement, which was most likely caused from encouraging the subjects to limit excessive body motion [12].
This study is an attempt to distinguish EEG signals during two states of mind: idleness versus mental math calculation. The results provide information helpful in designing future EEG-based BCI that can recognize specific cognitive states and learning emotions during mathematic performance. With further development to improve EEG signal acquisition and processing, this technology could then in turn be used to design intelligent tutoring systems aiming to improve classroom environments, teaching effectiveness, and math education overall.

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