



## **An Analysis of Students' Brain Activity when Participating in Different Learning Activities**

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## **1. Introduction**

Existing research has demonstrated the improvement in effectiveness of learning when specific teaching methods such as active learning activities are used, when compared with traditional passive instruction. Park and Choi state that in Technology Enhanced Active Learning (TEAL) classrooms, students demonstrate higher interest and engagement in class, as well as improved exam performance [1]. Freeman et. al. analyzed a significant amount of existing data from several studies on students' exam performance under traditional lecturing versus active learning and discovered that active learning strategies lead to a significant improvement in exam scores, specifically in science, technology, engineering, and mathematics (STEM) classes [2], [3]. There is also an increase in recognition and emphasis on experiential education and problem-based learning, both of which have been shown to lead to increased grades and positive feedback from students [4] – [7].

Among these studies, effectiveness of learning is mostly measured and quantified through exam scores, self-reported surveys, or focus group studies. However, traditional grade-based assessment introduces many limitations and biases in studying student's retention of knowledge and high-level understanding on the practical aspect of the contents [8]. Additionally, these traditional assessment approaches are limited to providing only after-the-fact feedback to the instructors. Studies have shown that some measure of cognitive load may be obtained objectively through the use of electroencephalography (EEG) by measuring the bioelectrical activity of the brain [9], [10]. EEG data has also been used to assess concentration and stress level [11]. With increasing accessibility of commercial-grade EEG devices, some researchers have used brainwave data as a means of analyzing students' engagement during various learning activities and determining the relationship between brain activities and test performance in small groups [12]. For example, Sun used an EEG device to quantify students cognitive load during the use of mobile polling [13].

EEG signals range from 0.5 Hz to over 30 Hz. Delta waves (0.5 Hz – 4 Hz) are the slowest, commonly detected when a person is in deep sleep. Theta waves (4 Hz – 8 Hz) are detected during meditation and quiet focus. Alpha waves (8 Hz – 12 Hz) occur during relaxation when awake. Beta waves (14 Hz – 30 Hz) indicate the state of thinking, excitement, and concentration. Gamma waves are less well studied but are related to high cognitive load [14]. Among these frequency bands, theta, alpha and beta wave power are closely related to cognitive processes [10]. These frequencies are of particular interest in this study.

In order to better study the factors that contribute to students' engagement and performance, we collected and analyzed students' real time brainwave data while students participated in several varied learning activities. This study, which is a work-in-progress, provides baseline data that will be used in developing requirements for the design of a low-cost EEG device to be deployed to a sample of approximately 30 students in a large lecture environment, for the purpose of studying students' engagement and attention levels, which together with other assessment results the authors hope will provide valuable feedback on instructional methods.

## 2. Methodology

The experiment was conducted in a first year (freshman) engineering design course at the University of Toronto. This design course included three one-hour lectures and one two-hour studio every week. The lectures were conducted in a large technology enhanced active learning (TEAL) classroom with 290 students. Studios are smaller size classes where the students work in groups of three to four students on a set of activities directed by the studio teaching assistants (TAs). Each studio contained six groups. Six participants (4 male, 2 female) were selected on a from 25 volunteers to participate in the first round of preliminary testing. This study has received Research Ethics Board approval via the Research Ethics Office of the University of Toronto.

An OpenBCI [15] Open Source EEG device was used for measuring and recording brain wave activity. Eight dry Ag/AgCl electrodes were placed at Fp1, Fp2, C3, C4, T5, T6, O1, and O2 positions based on the international 10-20 system. Two reference electrodes were placed on the ears. Dry electrodes were used to avoid the need for skin preparation, including the use of conductive paste, which is thought to be somewhat inconvenient to the participants. Data was captured using a sampling frequency of 250 Hz.

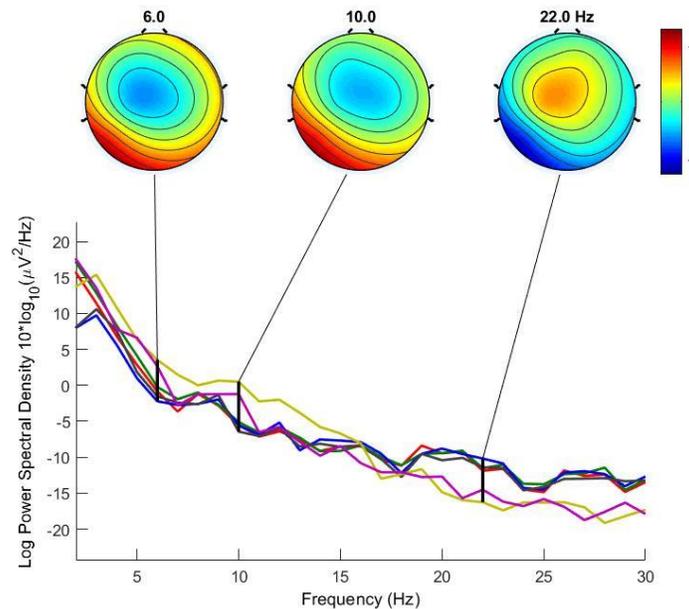
Prior to the experiment, a set of baseline data was captured by participants performing four 3-minute activities: participants keep eyes closed (EC); participants keep eyes open (EO) and maintain gaze focused on a cross on a white background; participants remain relaxed (RL) facing a blank wall in a quiet room; participants view a sequence of numerical digits displayed one-by-one and then input the digits into the system, referred to as forward digit span (FDS); participants play a Tetris™ game (TT) with an increase in difficulty level every minute. FDS tasks are commonly used to measure number storage capacity in working memory [16]. EC and EO are common baseline activities used for device calibration, RL, FDS and TT are selected to represent the relaxed and focused states for comparison with the experimental data.

Following initial baseline data collection, participant EEG data was recorded during 3 class sessions. For each learning activity, data was captured in 180 seconds windows and collected simultaneously on three students working in the same group. Except for group discussions, scheduled by the lecturer for 90 seconds each. Activities during the data collection sessions were categorized based on the learning format, including: didactic learning (DL); active learning: group discussions (GD), questions & answers (QA); and experiential learning (EL). The data collection durations are summarized in Table 1.

**Table 1** – Duration of data collected for different learning activity.

Class Session	Learning Style	Number of Sessions	Mean Collection Time Across Sessions (ms)
I	DL	5	185068
	GD	3	89612
	QA	3	184594
II	DL	5	171863
	GD	3	88257
	QA	3	174570
III	EL	5	182171

After removing the noise signal, power spectral analysis was performed by applying Fast Fourier Transform to each channel. The absolute power spectral density of each wave band was calculated and compared for different activities (Figure 1). To better represent the state of the participant, 90 seconds of data following the first 30 seconds in each activity session was analyzed from the baseline data and the DL, QA, EL data; 45 seconds of data following the first 30 seconds was analyzed from the GD sessions. Channels with poor signal quality were rejected. 8 EEG channels were categorized to 4 brain lobes: frontal (Fp1, Fp2, C3, C4), left temporal (T5), right temporal (T6), occipital (O1, O2). For each learning activity and each lobe, the spectral power across all valid sessions and participants was averaged for comparison.

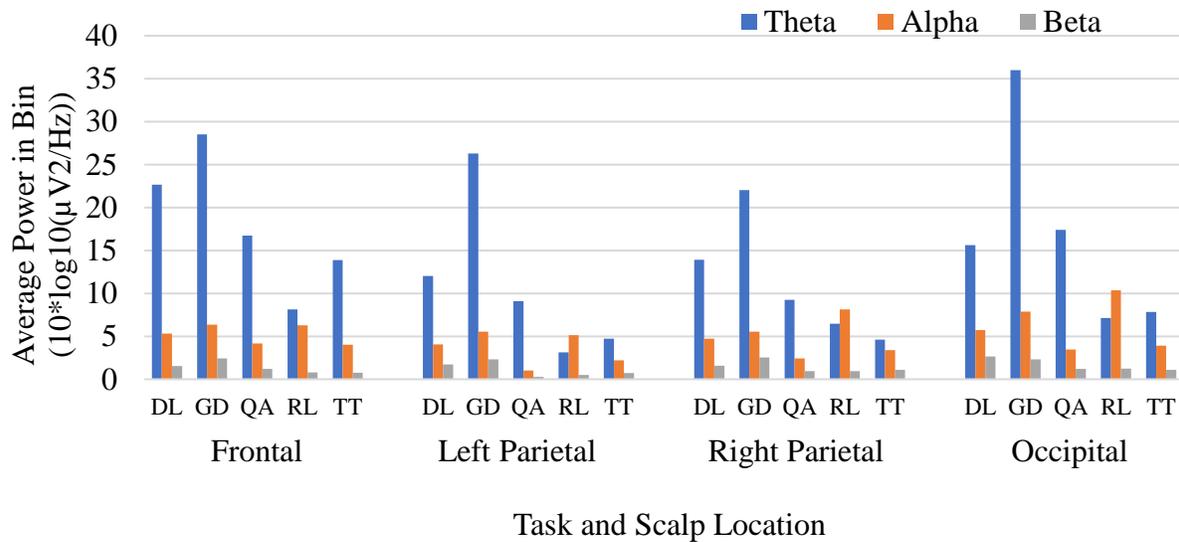


**Figure 1** – Power spectrums of all 8 channels during one DL session from one participant, with scalp map showing scalp distribution of power at 6 Hz, 10 Hz, and 22 Hz

### 3. Results

Due to both unforeseen delays and difficulties in the COVID-19 pandemic, the experiment was shortened. This has negatively influenced the sample size of this study so that, at the time of writing, data from three participants have been recorded and analyzed.

The experiential learning data was eliminated due to high noise. The participants were working in a group on a hands-on rover building project, in a busy fabrication facility environment. The amount of body movements led to poor signal quality, and it was challenging to ensure the participants were only performing experiential learning task at all the sessions in the busy environment. The average spectral power for the other three learning activities and two baseline activities are shown in Figure 2. Baseline activities RL and TT are selected to represent relaxed and focused states. Overall, alpha frequency is stronger in relaxed state and weaker in focused state. Across the learning activities, both theta and alpha power are higher across all brain lobes during GD, comparing with DL and QA.



**Figure 2** – Average power in three frequency bins (theta, alpha, beta) in different brain lobes across three learning activities (DL, GD, QA) and two baseline activities (RL, TT)

#### 4. Discussion

The baseline activity result shows a difference between relaxed and focused states. However, it is difficult to identify any significant trend from the power analysis on the data collected during different learning activities. This is mainly due to the following limitations listed below.

A small sample size of three participants introduces biases. In the next step of this study, a larger sample size will be used. This way an average could be taken when analyzing a general trend across a class of students engaged in the same activity at the same time. Brain to brain synchrony [5] and inter-subject correlation could also be analyzed in the future.

Averaging the spectral power across the activity sessions has its limitation. Different activity sessions have significant variation in results. As data was collected during regular in-class hours, there are many extraneous factors that could contribute to the difference in brainwave signal. Baseline data were collected in a quiet meeting room with the participant doing one single task, while in-class data were collected in a noisy and busy classroom setting, full of numerous distractions. During GD sessions, different discussion topics, high noise levels as well as many other factors beyond the researchers' control will likely have an influence on the participants' EEG signals. Additionally, the specific discussion topics across activity sessions varies, which will influence the participants concentration level. In the next step, power spectrogram will be generated with frequency versus time, in order to cross-reference the specific brain activity state and the real-world environment and activities.

Additionally, studying of an individual's focus state is challenging. Although focus state could be identified through the analysis of brainwave spectral power, in a large lecture environment, it will be challenging to identify the topic on which a participant's attention may be focused. For

example, aside from listening to the instructor, students frequently spend time on their electronic devices, or engage in quiet conversation with classmates. The researchers feel that there may be some significant value in studying the “unfocused” or “relaxed” state of students. For example, a metric of the level of unfocussed brain activity in a lecture could tell an instructor when too much time has been spent answering a particular student question, or when a favorite anecdote or recent research finding is not proving to be as engaging to the class as the instructor may believe.

## **5. Conclusion**

This preliminary study has provided insight into some of the challenges that will be faced when implementing a larger scale EEG study within a real-world learning environment. Particularly, this study has shown the challenges in identifying whether focused brain activity is in fact, focused on the “right” content, and has suggested a related avenue for future work in identifying the unfocussed EEG activity of students as a way of providing potentially valuable real-time feedback on the effectiveness of various teaching methods.

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