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Towards a Categorization of Brain Emotional-States using BCI

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Abstract

In recent years, Brain-Computer Interface (BCI) technology has made great strides, with more capable and less costly systems coming into the market with each passing year. The involvement of Big Tech companies, such as Neuralink[2], has firmly catapulted what was a fringe research community, into the mainstream. Most work in this area aims to build more intuitive user interfaces that can be operated by thought alone. We find that there has been relatively little effort towards building BCI systems that attempt to encompass the full range of the human experience, particularly with regards to emotions. This paper is a first attempt at redressing this imbalance.

Keywords: BCI; HCI

1. Introduction

The last couple of decades since the start of the 21st century has seen dramatic advances in human- computer interaction (HCI) as the two-dimensional graphical user interfaces (GUI) of the late 20th century have given way to augmented reality (AR), virtual reality (VR) and mixed reality (MR). We are, it appears, on the verge of fully immersive interfaces as envisioned in the push towards Metaverse systems. Whilst it remains to be seen whether such systems will live up to their hype and engender a society where everyone will seamlessly switch between a biological self and a virtual digital twin, the push towards bringing in such a global transformation of human society pushes ahead relentlessly.

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Whilst remaining irreplaceable for now for any serious work, traditional mouse-based computer systems have already begun to prepare for the MR future. We see desktop operating systems, for instance, having built-in support for face, speech and handwriting recognition, eye-tracking and even haptics. It is logical to conclude that computing “at the speed of though” is the next challenge that will be met, whereby an action is accomplished simply by thinking about it. The software and the associated nonlinear signal processing for brain-computer interfaces (BCI) become more capable and more affordable each year; equally, hardware sensors that pick up thought signals get smaller, more accurate and less intrusive.

Apart from the obvious applications of such developments towards more powerful ways and means to interact with computers (e.g., in games, education, etc.), there is also an enormous range of purely philanthropic applications which would allow those suffering from medical handicaps to live normal lives. This is particularly so for patients with total paralysis, whereby all motor control is lacking in a body with an otherwise consciously functioning brain. The development of BCI systems that allow such “locked-in” individuals to operate mobility or robotics-augmented prosthetics devices can surely be described as one of the most noble missions of the science and engineering community.

Historical Review

The application of physics, and specifically electricity, in the biological sciences has a very long history. As early as 1771, Luigi Galvani discovered that frog muscles contracted when struck by an electrical spark. Understanding of electricity and magnetism vastly accelerated during the 19th century, leading to many engineering advances. Carlo Matteucci and Emil Du Bois-Reymond were the first use a galvanometer to register the electrical signals emitted from muscle nerves, thereby essentially founding the science of neurophysiology. British scientist Richard Caton, reported the first known experiments on a range of animal species using galvanometer electrodes to study various physiological phenomena such as sleep, food and death in 1875.

Caton’s work went largely unnoticed for half a century. In 1924, however, it inspired Hans Berger, a Professor of Psychiatry at the University of Jena in Germany, to use the same galvanometer technique on a 17-year-old patient undergoing head surgery for tumor to discover that electrical signals existed at the scalp and could be measured. Berger refined his techniques for another five years and published a total of 14 articles on his discovery. By 1929, he had invented a scalp signal recording machine, and had coined the German term *electrenkephalogramm* to describe the graphical representations of the signals [2]. Berger’s radical suggestion was that these signals originated from currents in the brain, and that the dynamic nature of the signals were a consequence of the functional state (e.g., sleep, epilepsy, etc.) the brain was in. Nonetheless, the idea that these signals originated in the brain was only slowly accepted until Lord Adrian at Cambridge reproduced Berger’s results in 1934 [1]. Ironically, this did nothing to cement Berger’s rightful claim as the founder of the science of electroencephalography (EEG) as a basic tool of brain diagnosis and research, since the German government of the time shut down his laboratory and forced him into retirement just before the outbreak of the second world war.

Post-war research activity in EEG and BCI did not really take off in a significant way until the invention of the microprocessor and the commoditization of cheap computing hardware. Notwithstanding this, we note the following significant developments:

a. Jose Delgado invented a device he called a “stimoceiver” in the 1950s whilst at Yale. This was essentially a transceiver that received EEG signals and sent back instructions on dual radio channels. Delgado demonstrated this system in a famous experiment whereby he was able to stop a bull charging towards him simply by pressing a button.
b. Grey Walter in 1964 demonstrated a system for advancing projector slides using just electrodes attached to the motor areas of a patient’s brain. This essentially counts as the first ever BCI interface; unfortunately, Dr Walter did not publish his results, preferring instead to simply give a demonstration at a learned society meeting in London.
c. The establishment of BCI as a formal discipline of study can be accredited to UCLA computer scientist Jacques J. Vidal [7], who not only presented the concept of direct brain–computer communications using EEG signals and computer signal processing, but also coined the term “BCI”.

BCI as a popular discipline is truly a science of the 21st century. It was only in the early 2000s that the availability of cheap sensor technologies coupled with greater insights into brain functionality and better mathematical tools to handle nonlinear signals converged sufficiently to attract researchers and major funding.

BCI and Emotion-States

Whilst the drive to develop applications for the disabled has always been a key priority for BCI researchers worldwide, we find that there exist an equally active set of workers who are using the technology on perfectly healthy people. The objective of such “passive BCI” research is to be able to detect unintended changes in a user’s cognitive state as an input into other systems. As pointed out by Garcia-Molina *et al*. [4], precise awareness of the current emotional or cognitive state can affect the recognition of the mental task associated with the recorded brain waves – in other words consciousness is a driver of emotions. Application scenarios that use passive BCI can thus be fine-tuned to utilize the best control that could be used in a given situation.

Emotions, plainly speaking, are reactions that humans experience in response to events, situations or other real or artificial stimuli. Psychologists define emotions formally as “a complex reaction pattern, involving experiential, behavioral and physiological elements” – we note here the specific mention of *physiological* elements. Emotions, clearly, have a powerful effect on the human body. The study of emotions has largely been the domain of the social sciences, spanning disciplines from psychology to philosophy. The development of a universally accepted model to categorize emotions remains, for now, a task for interdisciplinary science.

As such, no rigorous mathematical definition of emotions exists at present, although lots of theories have been advanced. We propose that a simple engineering approach to categorizing emotions would be to treat an “emotion-state” as a point in discrete emotional state space, and to model complex sets of emotions as a linear superposition of a core set of “bases” emotions – this approach has the immediate benefit of opening up the formidable mathematical toolbox of linear vector space theory to the analysis of emotions. Indeed, we find that the idea of bases emotions is supported by the psychology literature, where we find similar reductionism at play. Plutchik [5] identified a bases set of just eight emotions: acceptance, anger, anticipation, disgust, joy, fear, sadness and surprise. Ekman [3] reduced this set further to just six: anger, disgust, fear, joy, sadness and surprise. Other psychology theorists have proposed a continuum of emotional states, along multiple dimensions (see, for instance, Russel [6]).

Since we have in EEG-based BCI systems a powerful technology to probe the human brain's mysteries in a clean and noninvasive way, the question arises as to whether it would be possible to test out and establish the existence or otherwise of ideas about emotion-state bases through such systems. This paper is a first attempt at just such an undertaking.

Procedure

Our study used a commercial off-the-shelf, and minimally invasive, EEG technology to monitor the emotional response of various subjects during clearly-defined emotion-inducing psychological tasks. Our goal in these measurements was to investigate the possibility of measuring and subsequently categorizing the subject's emotional state using the BCI device. If consistent metrics of classifiable emotional states can be determined this way, it opens the way for many newer forms of HCI in a range of areas, for instance automated assessment and training.

Participants

As this set of findings was intended primarily to demonstrate proof-of-concept[3], we restricted this study to the following test subjects, experiencing a limited range of just four emotion-states, as follows (Table 1):

	9 year-old female	22 year-old female	48 year-old male
SAD	✓	✓	✓
HAPPY	✓	✓	✓
TENSE	✓	✓	✓
MEDITATIVE	✓		✓

Table 1: Emotional States Targeted for Test Participants

Equipment

The BCI equipment used in our setup consisted of an OpenBCI Cyton board interfaced to a COTS EEG cap with dry electrodes.

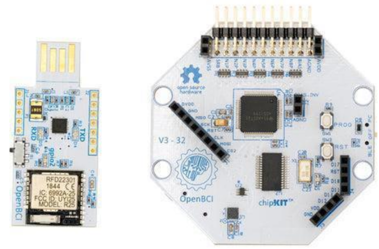	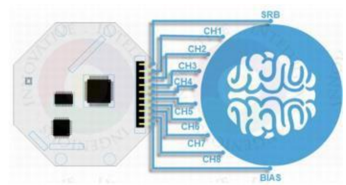	
Wireless EEG Module Cyton Biosensing Board 8-channels for Open BCI DIY Brainwave Arduino Kit.	OpenBCI has 8 independent signal acquisition channels (each channel has two signal ends, one for the reference, and can be configured for multiple different channels common or independent use of the reference end).	Flexible brain electric EEG Cap with dry Electrodes, Compatible with OpenBCI Ultracortex_Mark Series EEG Caps.

Figure 1: Overview of the BCI hardware used in our work

The OpenBCI Cyton Board is an Arduino-compatible, 8-channel neural interface with a 32-bit processor. At its core, the OpenBCI Cyton Board is built around the PIC32MX250F128B microcontroller. The OpenBCI Cyton Board can be used to sample brain activity (EEG), muscle activity (EMG), and heart activity (ECG). The board communicates wirelessly to a computer via the OpenBCI USB dongle using RFDuino radio modules (Figure 1).

The software application we used was the open source OpenBCI application, freely available at: https://github.com/OpenBCI/OpenBCI_GUI.

Experimental Procedure

An emotion is a human body response to a trigger that has to be elicited. The stimuli that elicit such responses are best delivered through the medium of digital video, since the human mind responds to *dynamic* information more readily than it does to *static* information. Over the last few years, the enormous growth in AI and Data Science has given rise to a range of open-source databases with standardized image datasets for training and evaluation of neural models. Unfortunately, such standardized *video* datasets are presently not available, to the best of our knowledge, to test emotion-states[4]. We had to work instead with freely-available Internet video resources to elicit the SAD, HAPPY and TENSE emotion responses. The MEDITATIVE state was induced through a recitation of the Qur'an.

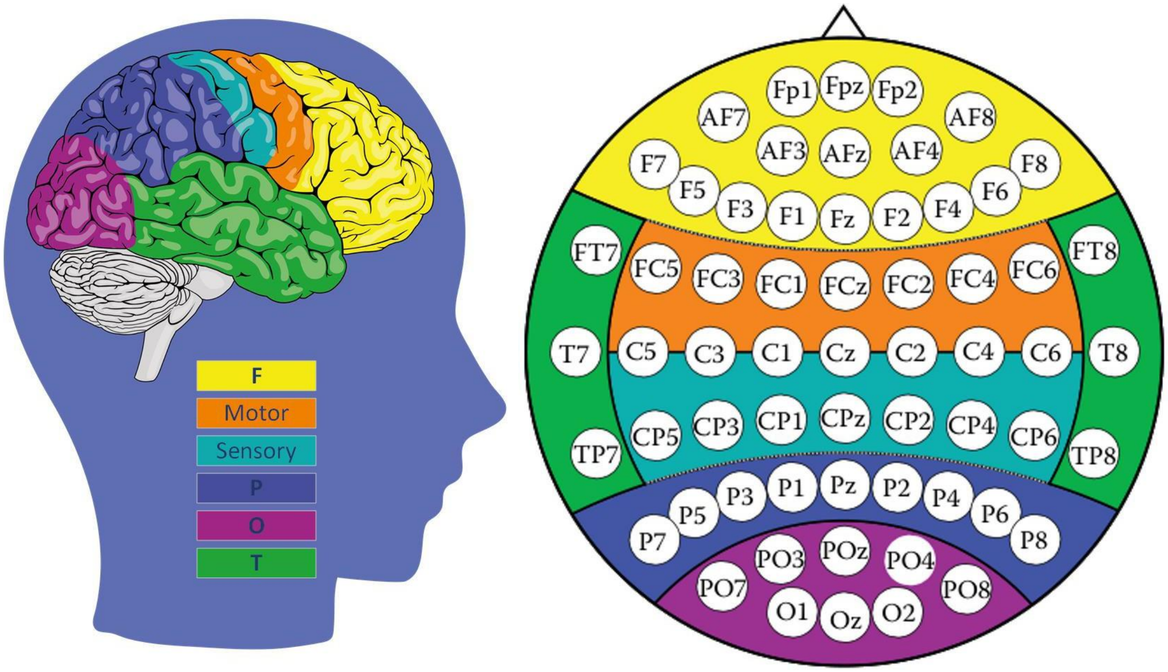

Figure 2: Standardized Labels of Electrode Positions on the Human Head.

The sensor positions as depicted in Figure 1 are based on the standardized international "10-20" classification system (see, e.g. Nang *et al*., 2018, on which this is based). We note the following:

- The electrode labels are composed of letters and a number;
- The letters correspond to anatomical structures, the **F**rontal lobe, the **P**arietal lobe, the

  Occipital lobe, the **T**emporal lobe, and the **C**entral sulcus;
- The "rows" of electrodes centrally over those structures are denoted with the corresponding single letter. These principal electrode rows are positions that are specified as percentages of the distance between the boundary endpoints of the sensor array;
- Rows between those principal rows have two-letter labels, the first one being the one from the row that is more frontal: for instance, "FC" denotes between the "F" and the "C" rows;
- The rows anterior to the "F" row are denoted by "AF" (Anterior Frontal) and "Fp" (Front-polar);
- The position in the left-right direction is specified by numbers, the odd ones going from the vertex down the left hemisphere, the even ones going from the vertex down the right

hemisphere, and the vertex itself indicated by the letter "z" for zero.
In our work, only the following nodes were used: AF3, AF4, F3, F4, F7, F8, T7, and T8. Use of this set guarantees up to 85% accuracy in the measurements.

Results

EEG studies of the brain identify five different types of waves, each with its own characteristic frequency range, as shown in Table 2.

Wave Type	Frequency Range	Physiological Characteristic
Delta waves	1 Hz to 3 Hz	Deep Sleep
Theta waves	4 Hz to 7 Hz	Drowsiness / Creativity / Meditation
Alpha waves	8 Hz to 12 Hz	Relaxed
Beta waves	13 Hz to 40 Hz	Thinking, Active Problem-solving
Gamma waves	41 Hz to 100 Hz	Abnormalities / Anxiety

Table 2: Brain Rhythms and their Characteristics.

In Figures 2 to 5, we present our observations for the four emotion-states of Table 1 for the three test subjects, where we have identified the dominant brain rhythms in light of the data in Table 2.

Discussion of Results

The most striking deduction from our tests is the clear difference in responses between the young and the adult subjects. We also note that there are identifiable differences between the male and female subjects. Specifically, for the four emotion-states, we find the following:

- SAD: The adult female is anxious, the young female is in a thinking/anxious mode, and the adult male is largely in a thinking mode.
- HAPPY: The adult female is relaxed, the young female is relaxed/creative, whilst the adult male is relaxed and meditative.
- TENSE: The adult female is actively thinking, the young female is relaxed with some thinking, the

adult male is Creative but relaxed.

- MEDITATIVE: The young female is relaxed and thinking, whilst the adult male is actively thinking but also relaxed.

2. Conclusions

In this paper, we have measured EEG brain waves for identified emotional stimuli for a test group of young and adult persons, both male and female. We have observed a clear difference in response within the group to the same set of stimuli – clearly, gender and age differences both play a significant role in the emotion-state that results from a stimulus.
For the future, we aim to extend the study to cover the following scenarios:

- More emotional states, as, for instance identified in the professional psychological research literature;
- The use of a larger test group of subjects, specifically in 10-year gaps, to cover age ranges between a young child to an elderly person;
- Use of filtering and signal processing to provide greater understanding of the observed emotional responses;
- Dynamic emotional states, where the stimuli are slowly altered over time – a key objective here would be to observe the speed of transition between states, and also to observe mixed emotional states that may or may not respond to a superposition of brain rhythms.

3. References

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[5] Plutchik, R., "A General Psychoevolutionary Theory of Emotion", in *Emotion: Theory, Research, and Experience.* **Vol. 1,** Academic Press, N. Y., 3–33 (1980).
[6] Russel, J.A., "A circumplex model of affect", Journal of Personality and Social Psychology, **39,** 1161–1178 (1980).
[7] Vidal, J.J., "Toward Direct Brain-Computer Communication". Ann. Rev. of Biophysics and Bioengineering, **2;** 157-180, https://doi.org/10.1146/annurev.bb.02.060173.001105 (1973).

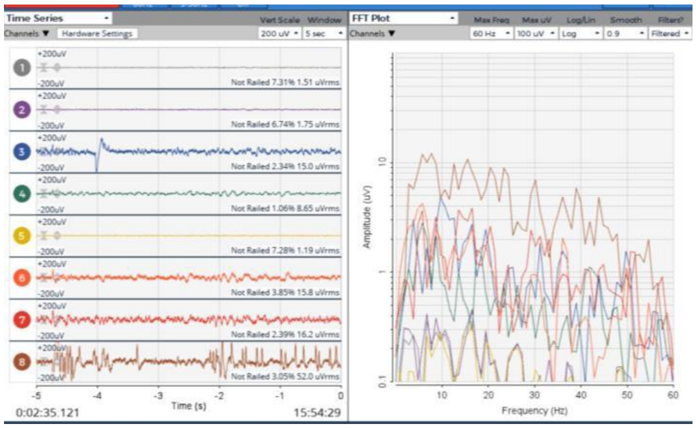
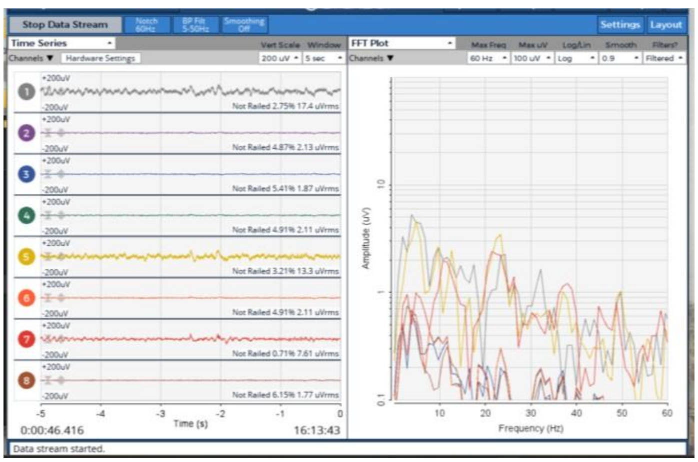
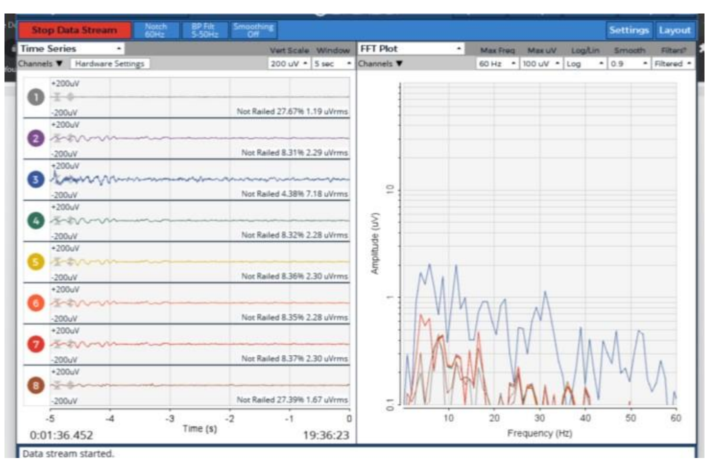
	**Emotion-State**: SAD **Subject**: 22 year-old Female **Observation**: High Gamma
	**Emotion-State**: SAD **Subject**: 9 year-old Female **Observation**: High Beta, some Gamma
	**Emotion-State**: SAD **Subject**: 48 year-old Male **Observation**: High Beta

Figure 3: BCI readings for emotion-state SAD.

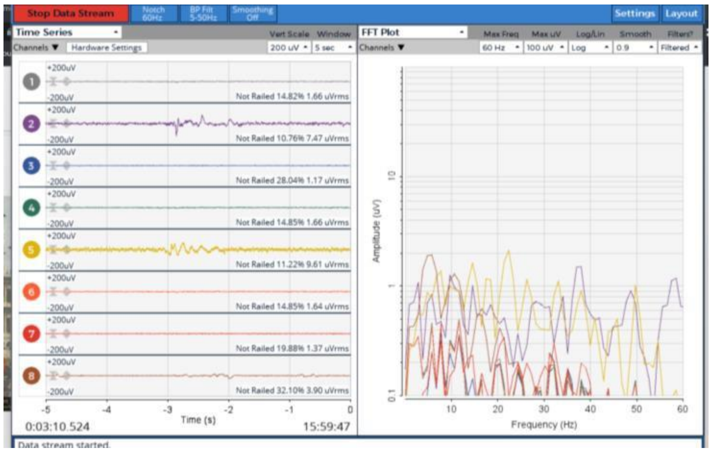
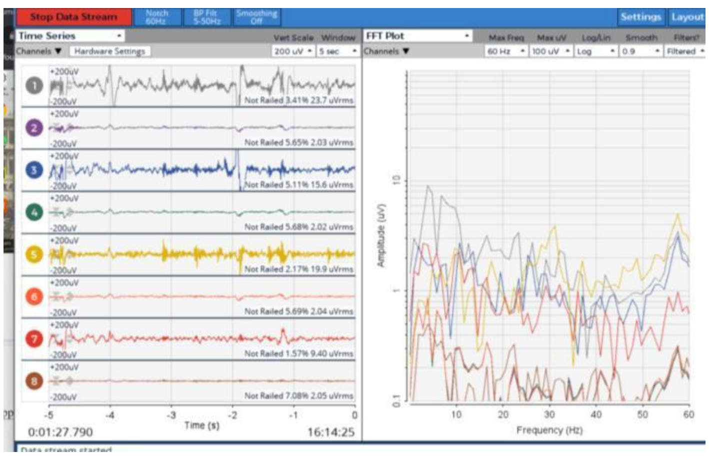
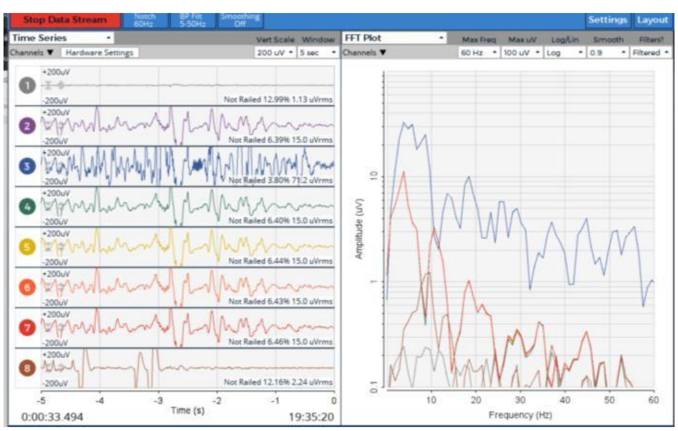
	**Emotion-State**: HAPPY **Subject**: 22 year-old Female **Observation**: High Alpha
	**Emotion-State**: HAPPY **Subject**: 9 year-old Female **Observation**: High Alpha, High Beta
	**Emotion-State**: HAPPY **Subject**: 48 year-old Male **Observation**: High Theta, High Alpha

Figure 4: BCI readings for emotion-state HAPPY.

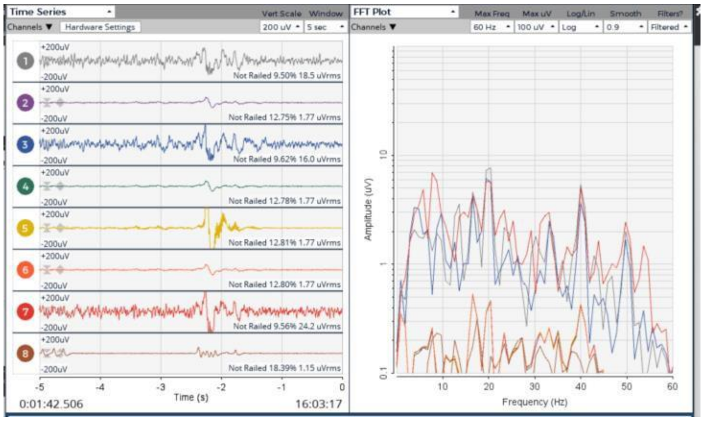
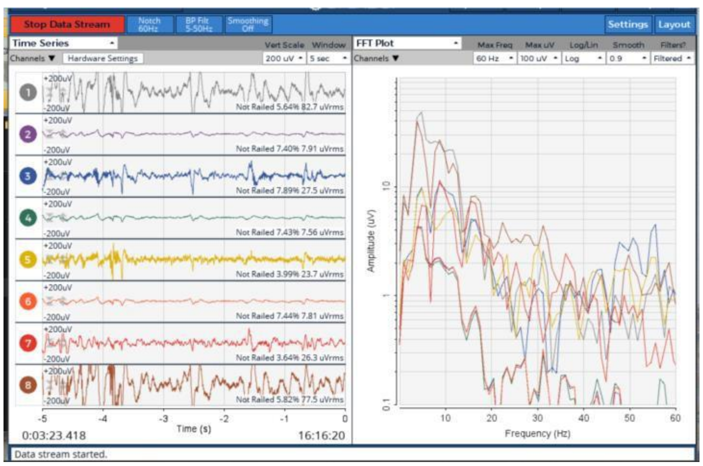
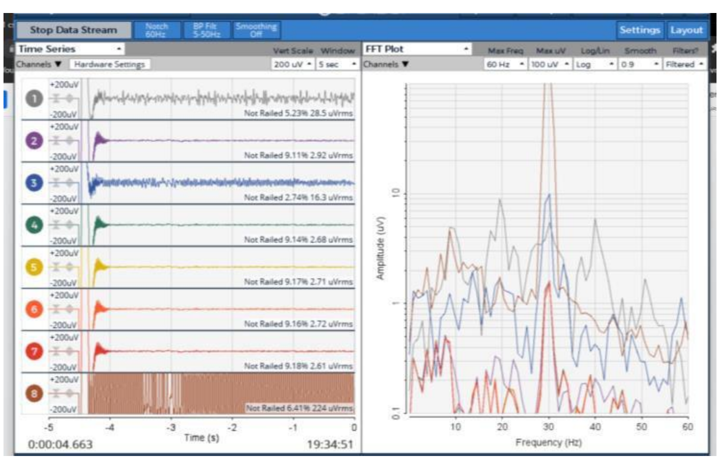
	**Emotion-State**: TENSE **Subject**: 22 year-old Female **Observation**: High Beta
	**Emotion-State**: TENSE **Subject**: 9 year-old Female **Observation**: High Alpha, Some Beta
	**Emotion-State**: TENSE **Subject**: 48 year-old Male **Observation**: Very High Beta, Some Alpha

Figure 5: BCI readings for emotion-state TENSE.

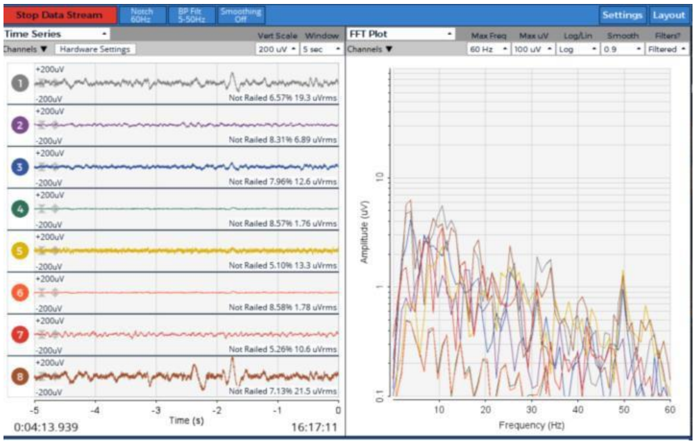
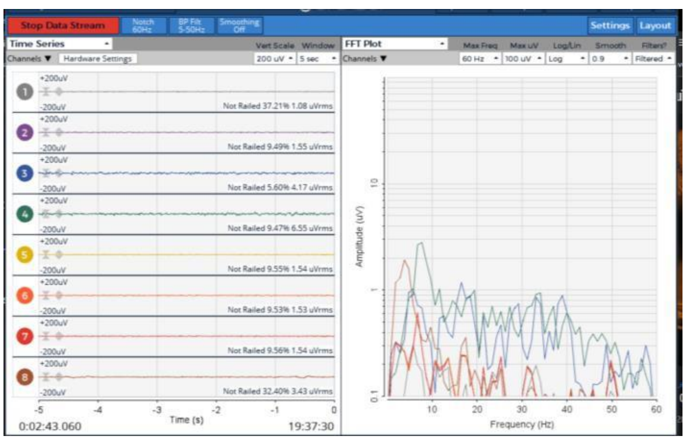
	**Emotion-State**: MEDITATIVE **Subject**: 9 year-old Female **Observation**: High Alpha, High Beta
	**Emotion-State**: MEDITATIVE **Subject**: 48 year-old Male **Observation**: High Alpha

Figure 6: BCI readings for emotion-state MEDITATIVE.