ECSE-457
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NeuroMantics
Neuro-feedback System to Improve Brain Health of Users

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1.Abstract

Neurofeedback is a subcategory of the broad field of biofeedback, which is the term used to define the practice of measuring different physiological functions of the body such as heart rate, blood pressure, skin temperature and neural activity to allow people to better control these processes at will. Neurofeedback deals specifically with monitoring the activity in the brain. There are various different methods of neurofeedback and they include Magnetic resonance imaging (MRI), Functional Magnetic resonance imaging (fMRI), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS) and Electroencephalography (EEG) Neurofeedback. The implementation of these differ greatly in the cost and setup requirements. In our project we focus on neurofeedback using EEG, and do not discuss the other methods because they are substantially more expensive to implement and require a high degree of expertise. The specific field of using EEG to enable neurofeedback has seen an increase in popularity in the last few years and has seen a movement from clinical applications to more commercial applications, mainly due to availability of cheaper hardware. In this report we outline the design procedure implemented in building our neuro-feedback system from signal acquisition, processing, feature selection, feature classification and a human-computer interaction component.

2.Table of Figures

3. List of abbreviations

ADHD - Attention Deficit Hyperactivity Disorder
EEG - Electroencephalography
fMRI - Functional Magnetic resonance imaging
fNIRS - functional near-infrared spectroscopy
MEG - magnetoencephalography
MRI - Magnetic resonance imaging

4. Introduction

Sections 4, 5, 6 and 9 draw heavily from sections from the report. [1]

EEG (Electroencephalographic) based neuro-feedback refers to the field of using EEG signals to monitor the neural activity of a user and in turn use it to train a user to have better control over this activity. It has a range of applications but one of the fields in which it has found a lot of success is in the cure of Attention Deficit Hyper Disorder (ADHD). Attention deficit/hyperactivity disorder (ADHD) is characterised by developmentally inappropriate levels of inattention, impulsiveness and hyperactivity. It is generally agreed now that these characteristics are secondary outcomes of an underlying neurological disorder. The neurological disorder is thought to be characterized by increased slow 4-8 hertz theta activity in frontal and central cortical regions of patients. [4]

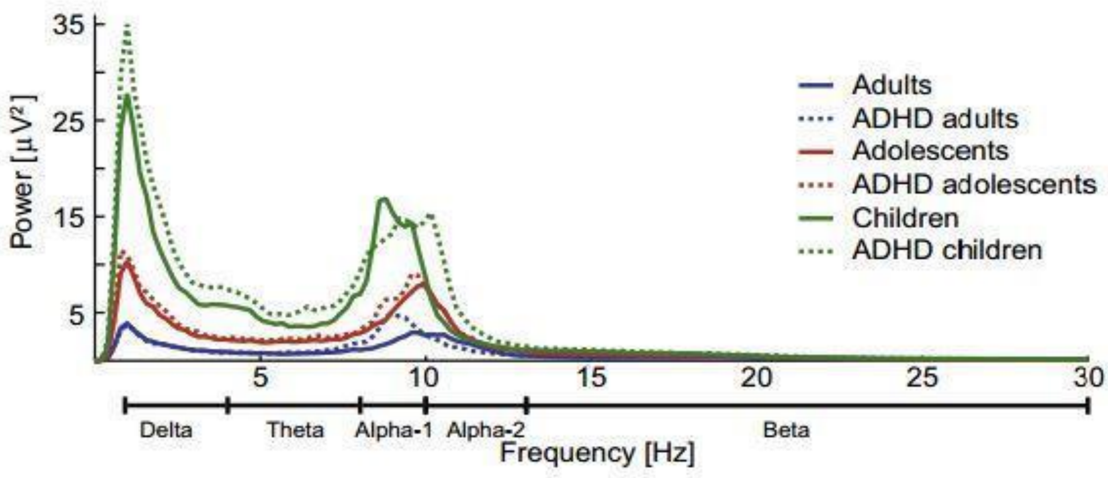

Figure 1: Comparison of wave bands of ADHD people with non ADHD people [10]

While there has been widespread literature that supports the claim that EEG based neurofeedback is a reliable tool to improve the brain health of patients with ADHD, there has also been literature that remains skeptical about it. In [5] it is mentioned that more research needs to be conducted with the proper control conditions and placebo considerations before neurofeedback can be accepted as a true cure for ADHD.

Neurofeedback has traditionally been a clinical field and the motivation behind the project is to engineer a more commercially applicable product that will empower people to improve their attention span through a dynamic and engaging application. While the discussion of its efficacy as a health tool remains unsettled, in this report we outline a design for a Neuro-feedback system that allows any user to engage their mind to control a brain-computer interface with a reward system in form of a game that rewards high levels of attention and penalizes a distracted state.

5. Background

5.1. Hardware

There are three main hardware requirements for a simple EEG neurofeedback system;

- The electrodes placed on the scalp to get electrical signals from the brain
- Amplifiers that amplify the signal
- Micro-controller which processes this signal and sends it to a computer or mobile

While this system can be quite expensive to set up in a lab for medical purposes, recent advances have allowed such systems to be available to the public at low costs.

5.2. Signal Processing

To be able to identify and distinguish between the mental states of the user, the raw EEG signal recorded by the headset needs to be processed and analyzed in real-time. However due to the noise and complexity of the signal this becomes a strenuous task.

Getting the most accurate estimations of mental states involves two steps. The first step is called “feature extraction”, which characterizes EEG signals using a number of values known as “features”. These features would ideally represent information contained in the signal, while filtering out the noise and unwanted information. There are three most common types of information that can be obtained from EEG signals are:

- Spatial information: These features would represent where the signals are coming from. This would usually entail analysing specific EEG channels and concentrating on specific areas of the brain.
- Spectral information: These features describe the variations in power for specific frequency bands.
- Temporal information: These features depict the variations in the EEG signal over time.

The second step is responsible for classifying all features extracted from the signal and aligning them with their corresponding metal state.

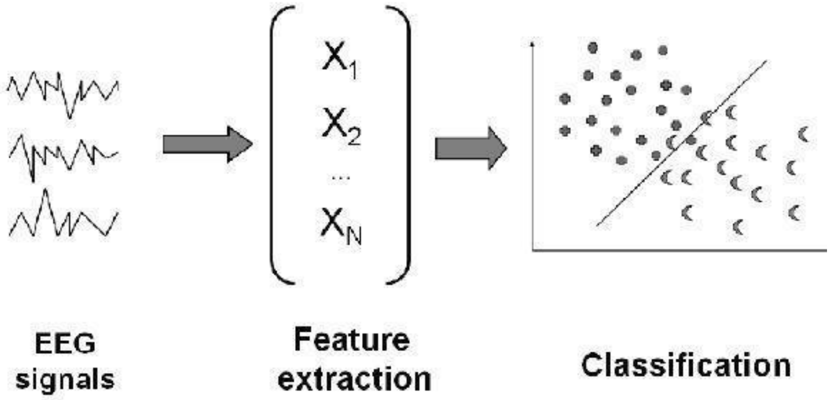

Figure 2: EEG Signal processing steps [8]

As EEG signals of users vary immensely, various machine learning approaches are used to fine-tune the algorithm responsible for the extraction and classification of the features. Supervised-learning approaches are used to carry out this task. This is done by providing sample data known as training sets which are labeled with their respective classification or mental state. This allows the algorithm to recognize and learn the classifications of each training set enabling it recognize unseen EEG signals. [8]

5.3. Human - Computer Interaction

After the signal processing stage and feature extraction states, we want to present a user with a dynamic and engaging interface which will enable them to see the state of their neural activity and also reward a focused state of mind. The human-computer interaction is an important part of the project as it is the part which really shifts the application from a clinical application to a more commercial application.

6. Requirements

6.1. Hardware

The process of collecting data EEG data starts with the electrodes which are placed on the user's scalp. The current produced by the movement of ions in the cerebral fluid and brain tissue is very small is very small and in the order of a couple of microvolts. Furthermore, there is the thick layer of scull and skin between the brain and the electrodes, which creates a high amount of impedance in the range of 150-200 KΩ.[7] The desired impedance for good EEG analysis is 5KΩ-20KΩ. The electrodes used in EEG analysis are therefore designed to minimize this impedance.

These electrodes come as either ‘wet’ electrodes or ‘dry’ electrodes. Wet electrodes refer to electrodes generally made from silver/silver-chloride (Ag/AgCl) and which require a special electrolytic gel to be applied to the scalp to ensure good electrical conduction. This can prove cumbersome and requires a lot of preparation and often the presence of specialists is required. Dry electrodes are made from various materials including Silicon, Gold, Titanium and Polyurethane. [6] They make the use of small spikes extruding from electrode which come in direct contact with the scalp, hence increase the total surface in direct contact with the scalp and reducing impedance. Dry electrodes have seen great improvements in the recent years and are one of the reasons that EEG-based neurofeedback is finding its place outside the clinic, and are more appropriate for our purposes.

After the electrodes get the current from the scalp, the signal goes through multiple steps before it can be seen in any useful form. A block diagram of an EEG system can be seen in figure 3. Since the current produced by the neurons in the brain is so small, the noise in the signal would make such a signal useless, therefore it is input into a differential amplifier with the other input being a reference electrode, which is often put behind the ear of a user. The gain of this amplifier is approximately 10 times. The output from this amplifier goes through another amplifier where the gain is often in the range of 100-200 times. After this, the signal goes through some further filtering, is digitized at 12 or 16 bits and then is transferred to the computer through some sort of communication protocol. [3]

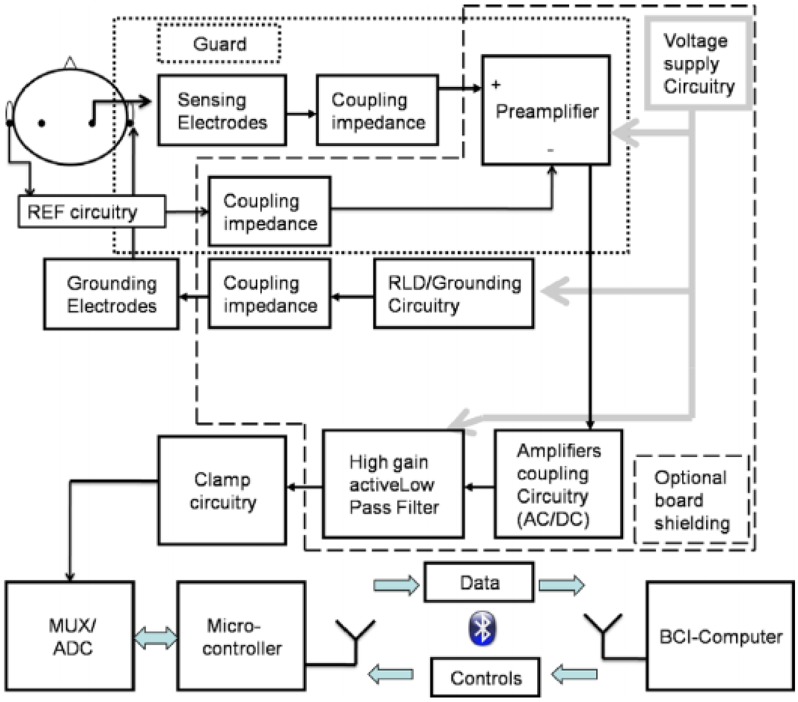

Figure 3: EEG system hardware block diagram [5]

The most common system for placement of the electrodes on the scalp is called the 10-20 system and is shown in figure 1.

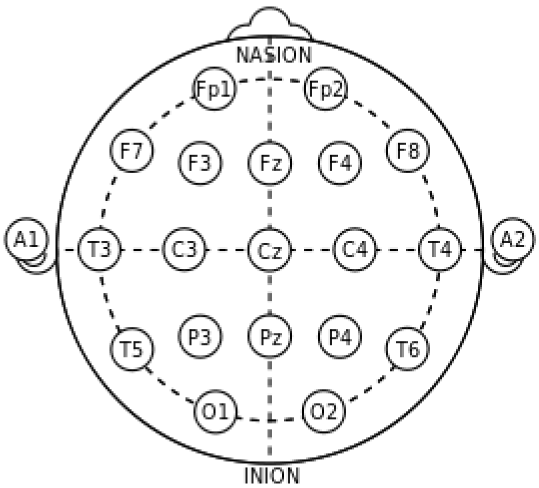

Figure 4: International 10-20 electrode placement system

6.2. Signal Processing

6.2.1. Feature extraction

The input to the signal processing algorithm in our neurofeedback application are raw EEG signals transmitted by the EEG headset. Since the raw EEG contain a lot of unwanted information and noise, feature extraction is used to decode these signals and represent them by a small range of values which contain the information relevant to our cause. Figuring out how to extract EEG signal features and then selecting the ones which would be most suited in our application would be a constraint for designing our algorithm.

6.2.2. Classification

In order to translate the extracted features into mental states a classification algorithm needs to be implemented with the help of machine learning. This classifier would attempt to model which ranges in a feature from a training set correspond to which mental state. There are two requirements for this part of EEG processing, firstly obtaining data sets of labeled mental states to train our algorithm. Secondly, choosing the classification algorithm that gives the most accurate result when faced with an unknown EEG signal.

6.3. Human - Computer interaction

An ideal interface for such an application is a gaming interface. The term used for such games is “serious games” and there are different routes which can be taken to create such game. The game engine Unity3D is an industry leader in building 3D games and has great tools available that make it compatible for use with EEG signals.

7. Design

7.1. Hardware

For the hardware, we compared many different low cost, commercial EEG systems including OpenBCI, Emotiv, Muse, NeuroSky and Cognionic. While comparing these options some key factors that we looked at were;

- Cost
- Freedom of electrode placement
- Availability of Raw Data
- Supporting Software libraries

After researching on this and contacting different companies, we decided that OpenBCI was the best choice for this project. it gave us numerous advantages over other options such as low cost, complete freedom to place electrodes, unlimited raw data, supporting libraries. We got their new Ganglion board which they released in January 2017. The board had 4 input channels + 2 reference channels, 200Hz sampling rate, Bluetooth 4 capabilities, and other features like accelerometer on the board.
The hardware specs [9] are listed below:

- Power with 3.3V to 12V DC battery ONLY
- Current Draw: 14mA when idle, 15mA connected and streaming data
- Simple BLE Radio module (Arduino Compatible)
- MCP3912 Analog Front End
- LIS2DH 3 axis Accelerometer
- MicroSD Card Slot
- Board Dimensions 2.41” x 2.41” (octagon has 1” edges)
- Mount holes are 1/16” ID, 0.8” x 2.166” on center
- Switches to manually connect/disconnect inputs to the REF pin

After experimenting with different electrode placement we set the electrodes at positions Fp1, Fp2, O1 and O2. Fp1 and Fp2 gave the cleanest signal as they were placed directly on the forehead. They also show good response to blinking of the eyes, and are a good place to measure event related potentials. O1 and O2 are associated with visual stimuli so showed the greatest response to visual images and hence were good for our application.

7.2. Signal Processing

The flow diagram below outlines the procedure we took for processing the EEG waves.

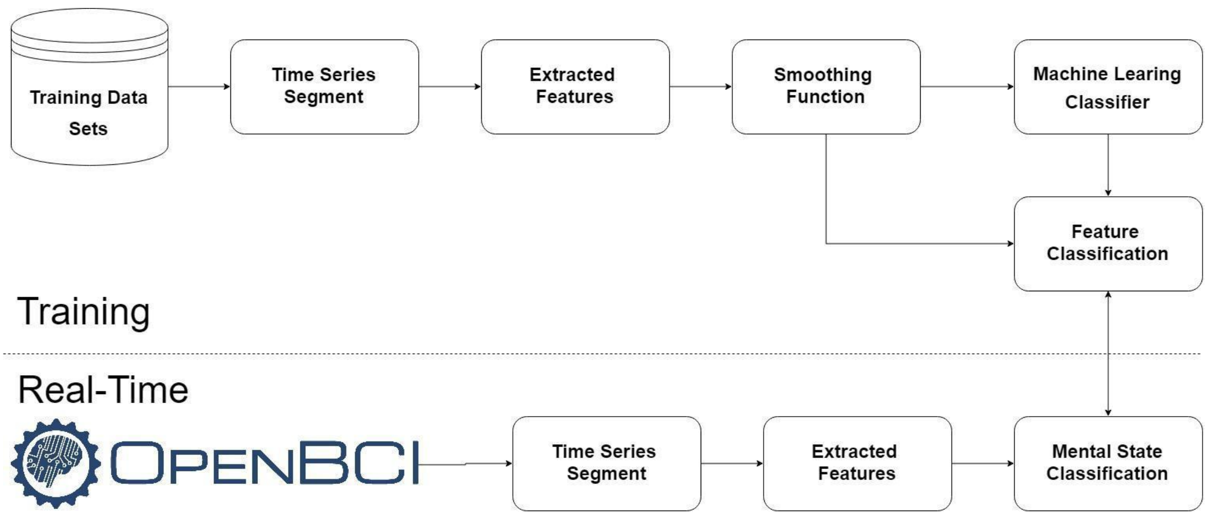

Figure 5: EEG signal processing flow chart

As soon as we had the Open BCI headset assembled we used PsychoPy, to programme an experiment in order to record data from various subjects. PsychoPy allowed us to present various mental exercises to our subjects in order to differentiate between their mental states. The experiment was divided into the following segments:

- 1.5 min – Mental math questions
- 1 min – Relaxed state
- 1.5 min – Pattern recognition multiple choice questions
- 1 min – Relaxed state
- 1.5 min – Focus on dot
- 2 min – Relaxed state

The timings in black represents a concentrated mental state whereas a relaxed mental state correlated to distraction; where the mind would wander and not think about the same thing for a long period. Ten data samples were recorded from all different subjects; 5 male and 5 female. The following plots show the 4 different channels from one subject:

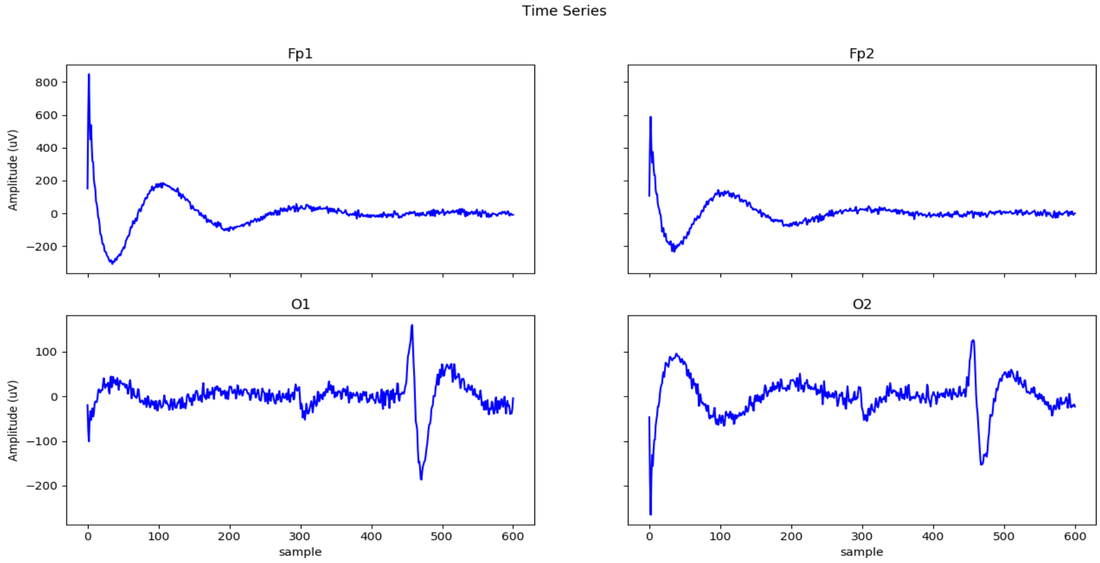

Figure 6: EEG Amplitudes from the Fp1, Fp2, O1, and O2 channels

After recording the data we separated each sample in respect to the concentration or distraction time frames and extracted their features.

7.2.1.Feature Extraction

A total of 15 features for each channel were extracted using the pyEEG library in python. The features were then plotted with the help of MATLAB to observe the trend of each feature. The features showing a significant difference in both states were kept while others were discarded. The features that were kept were as follows:

Theta/Beta wave ratios:

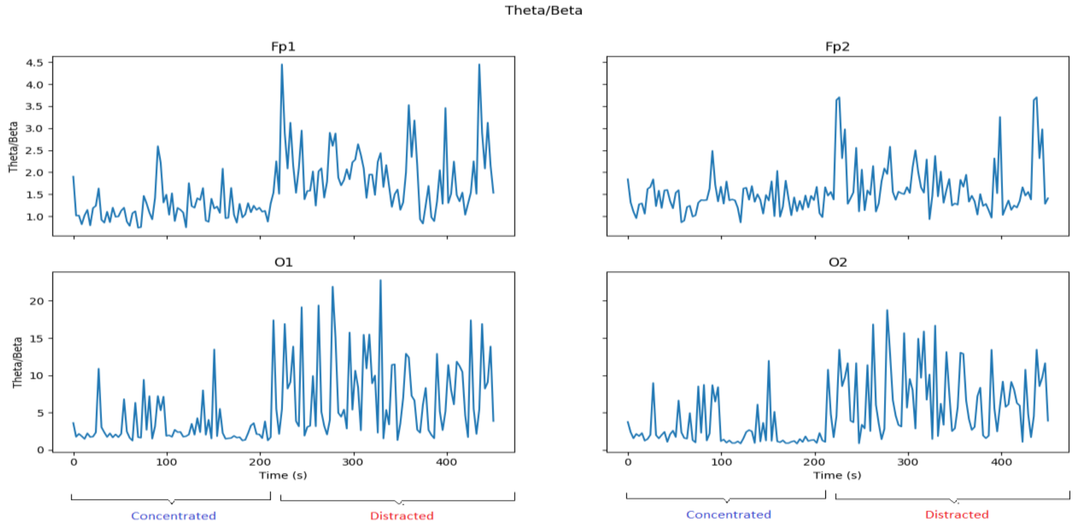

Figure 7: Theta/Beta wave ratios for concentrated and distracted states

Hurst Exponent: which is a measure of the long-term memory of a time-series. It basically quantifies the tendency of a time-series to either regress strongly to a men or instead cluster in a particular direction.

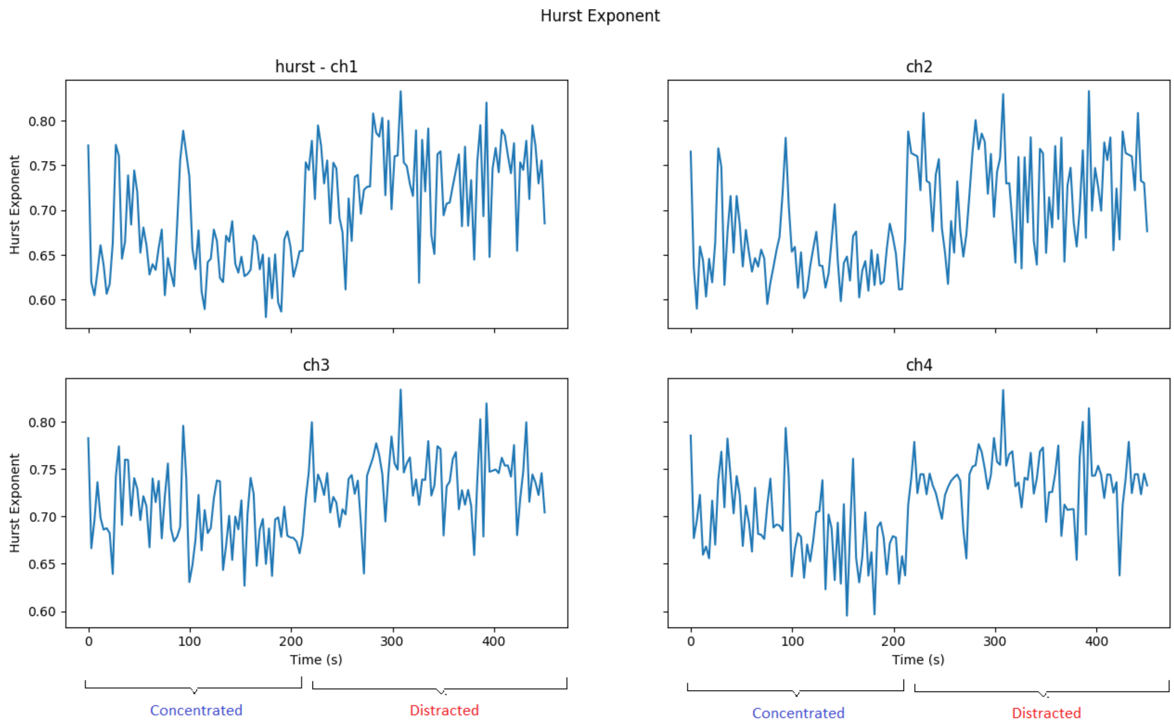

Figure 8: Hurst Exponent for concentrated and distracted states

Higuchi Fractal Dimension: Which is the measure of complexity and irregularity of the EEG signal. A higher fractal dimension correlates with a high complexity and vice versa.

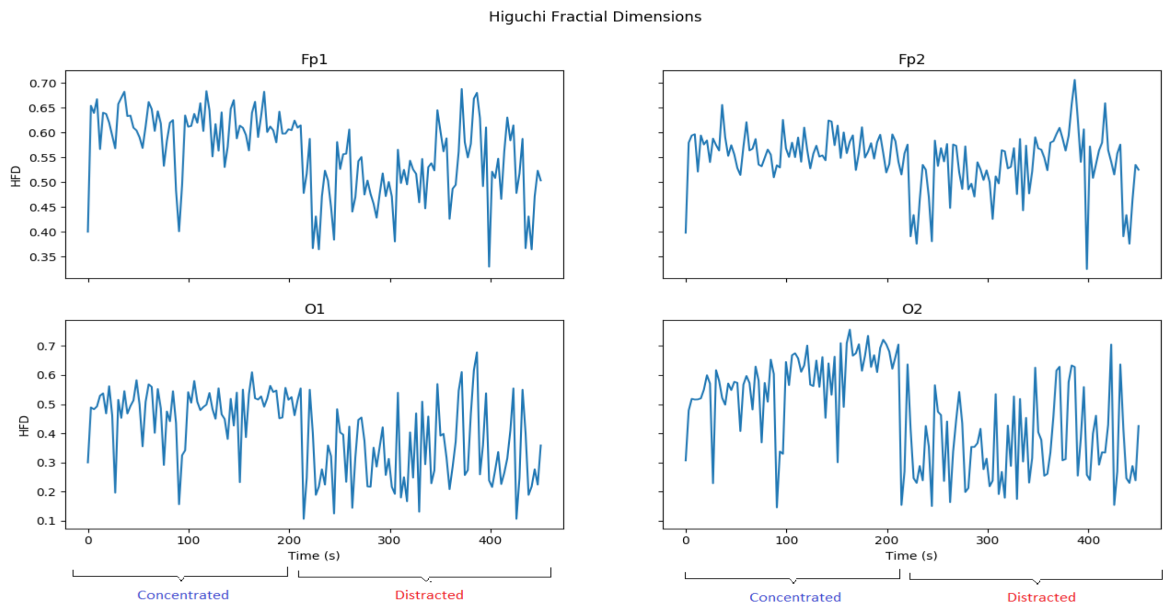

Figure 9: Higuchi Fractal dimension for concentrated and distracted states

As we can see from the above plots there is an obvious deviation in the trends for both mental states in all four features. One of the features that was discarded was the Petrosian fractal dimension. As we can see from its plot below that there is not a significant difference in its trend.

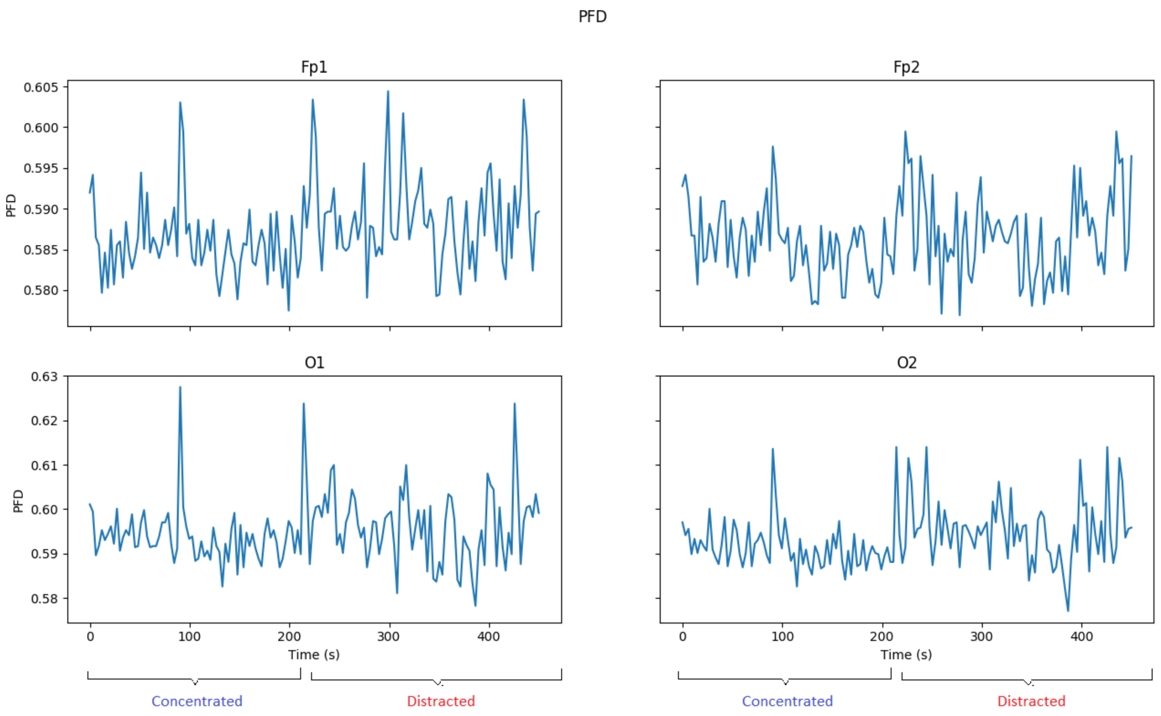

Figure 10: Petrosian Fractal dimension for concentrated and distracted states

However there is still a lot of noise and outlaw values which may cause inaccuracy in our application. Thus we adopted the Savitzky-Golay filter which acted as a smoothing function to remove noise and error-prone data points. The red line in the plot below shows the implementation of this filter on the Hurst Exponent.

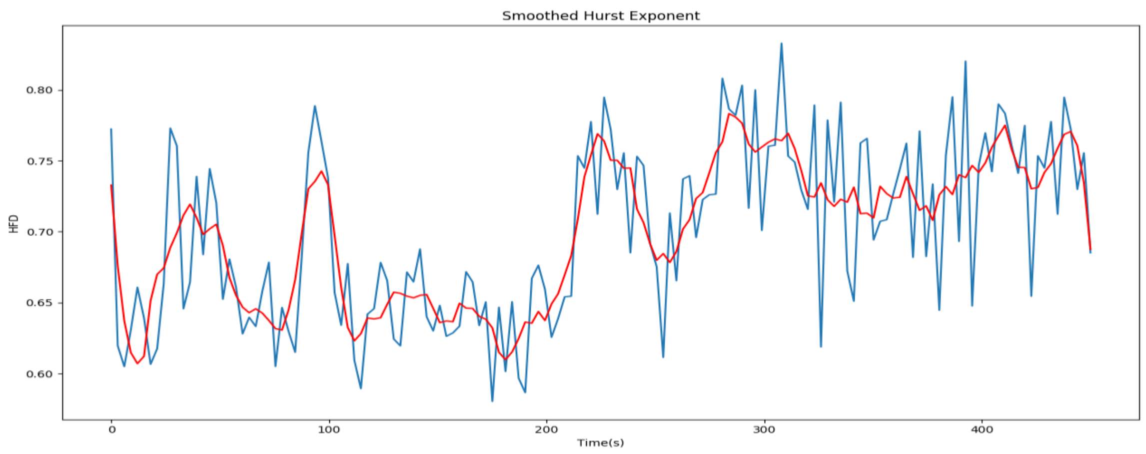

Figure 11: Comparison between Hurst exponent after using the Savitzky-Golay filter

7.2.2.Classification

Once we had the smoothened extracted features for both the concentrated and distracted mental states, we implemented a supervised machine learning approach in order to classify our data.

Since we only had two types of data to classify, we used linear supervised machine learning approaches with the help of the scikit-learn library in python:

- Support Vector Machines (SVM)
- Linear Discriminant Analysis (LDA)

Five random subject samples were used to train our classifier and the other five to test its accuracy.

7.3.Human - Computer Interaction

For the Human Computer interaction we built a game that would be an interactive and fun way for users to learn to control and maintain a concentrated state of mind. As ADHD is prominent amongst children and most curable at a young age, we believe that it is a good medium for them.

The game was designed using Unity3d and had only 2 inputs; the concentrated or distracted state of user. This information was fed to Unity in real time, from the python script that was implementing the signal processing and machine learning, using Open Sound Control (OSC). The reason for choosing OSC was that a large amount of data can be fed quickly in parallel so, while we were only sending very little information right now, in the future there could be a large amount of information that could be sent e.g. strength of different frequency bands and features, eye blink detection, accelerometer data from the headset etc. These can be used to add more features to the game.

The game was simple and the aim was to make an item on the floor rise when you are concentrated and fall when you are distracted. This way, the user feels like he is ‘moving the objects with his brain’ and thus wants to further maintain their concentration. There was also a score bar on the side which showed the current score of the user, and their high score which further motivated the user to maintain their concentrated state

Figure 12: Branch falls when distracted


Figure 13: Branch rises when concentrated

8. Results and Testing

The following figure shows the ROC for our machine learning algorithms:

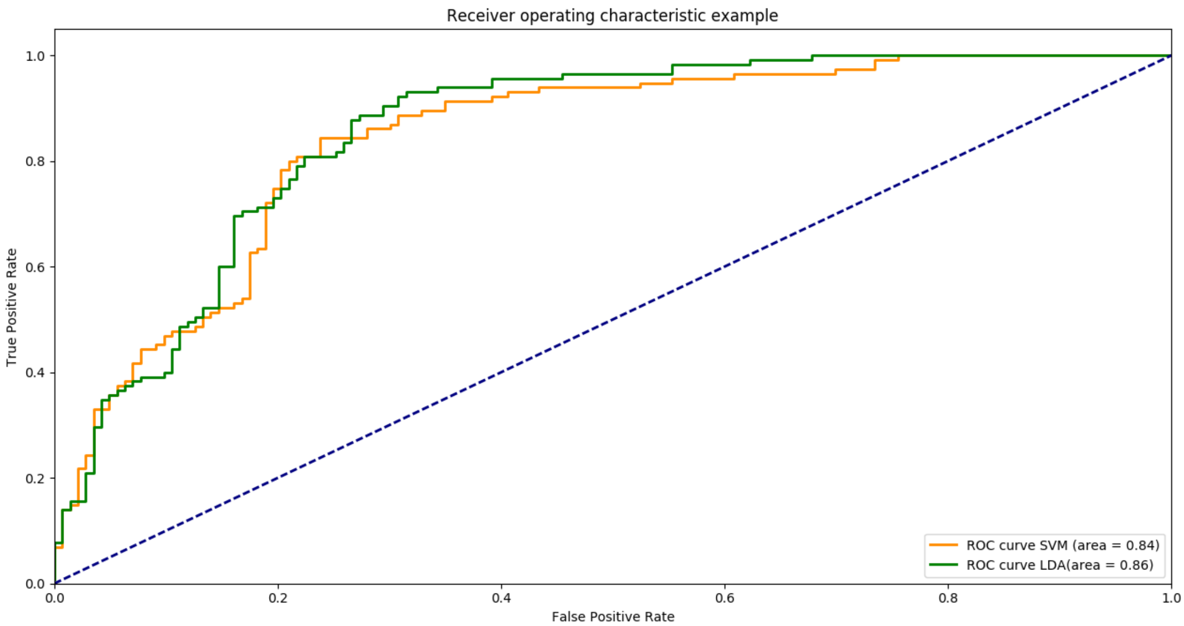

Figure 14: ROC for machine learning algorithms

We were able to achieve an 86 percent accuracy using our algorithm. We noticed that the greater the number of samples we used to train our data, the greater the accuracy got:

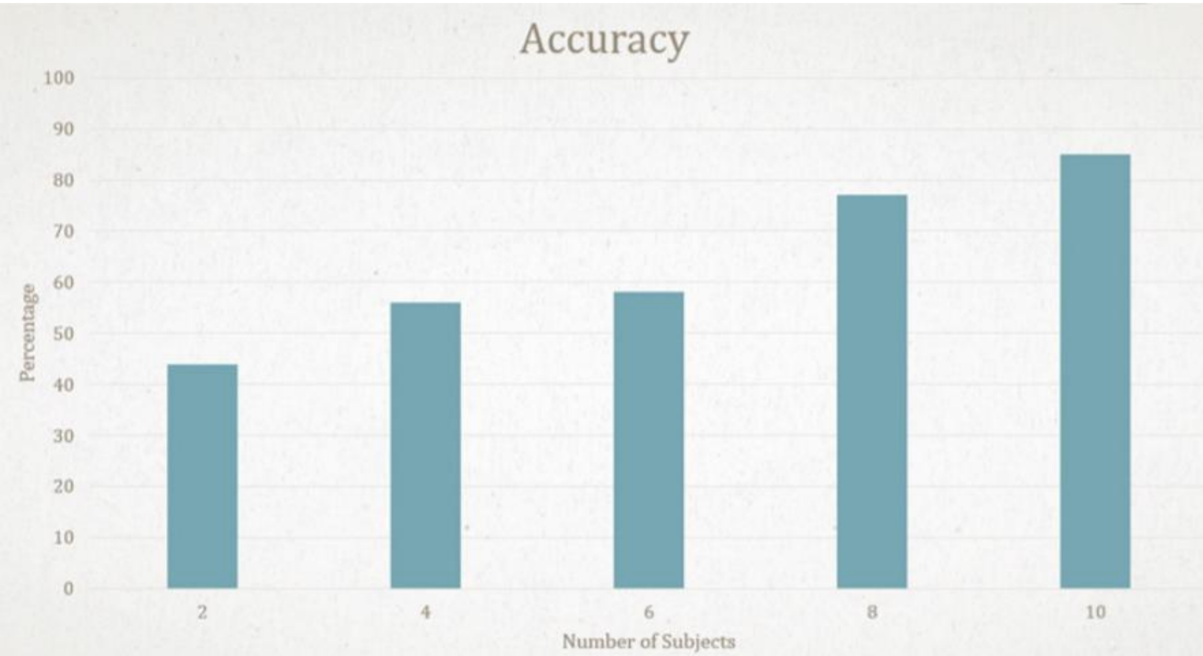

Figure 15: Accuracy against number of samples used in training

We tested our game on various subjects; those whom had contributed to the training data and those who had not. We discovered that for people who had not contributed to the training data, the game was more difficult in the start but in sometime were able to control their mental state and adapt. This could be because of less data samples used in training which led to our algorithm not being able to map all human thresholds which represented concentration.

9. Impact on society and environment

The final goal of our project is to improve the brain health of users, especially those with a neurological learning disorder. ADHD occurs in around 10 percent of people worldwide yet the majority of the world does not even recognize learning disabilities as an actual mental disorder. Even in Canada it is still vastly underdiagnosed and undertreated. While there is no cure for learning disabilities like ADHD they are manageable in a variety of ways. Despite this, due to this lack of diagnosis and treatment, the community generally fails to provide the services required to help these individuals. We want to empower people to be able to improve their brain fitness over time themselves at home.

Another aim of this project is to facilitate research in the field on neurogaming which is a new field and due to the advent of new platforms like virtual reality and augmented reality, is heading in exciting new directions.

There is no impact on the environment caused by our project. As we are focusing on optimizing the hardware aspect of the project as well, we want to be able to minimize energy consumption.

Neurofeedback through EEG is a totally non-invasive technique therefore there are no major health risks posed.

10. Report on Teamwork

The main areas of focus of both the team members are given below;

Muhammad Ammar Raufi

- ADHD and EEG
- Hardware setup
- Signal processing techniques
- Mental state classification
- Unity 3D – EEG game

Syed Irtaza Raza

- Recording EEG signals
- Machine Learning and EEG
- Testing
- Signal Processing

Since both of the authors come from an electrical engineering background, this field was new and exciting for both of them so they worked together on all the different aspects of the project. Syed is doing a minor in software engineering therefore he took the lead in the machine learning part of the research, while Muhammad took a lead in the hardware component.

They managed to keep a good level of communication by setting up space on Google Drive in the very beginning of the project where they were able to share papers and other documents with each other. They stayed in contact with their supervisor through email and tried to meet with him at least once a week for guidance and to relay progress reports.

11. Conclusion

In this report we have described the design process of a full EEG based Neurofeedback system from signal acquisition to the front end user interface. Using the OpenBCI kit we successfully collected EEG data from subjects, processed the data, compute features from it and then classified it into two distinctive mental states; concentrated and distracted. This classification enabled us to develop a real time feedback system in which the user's mental state was detected and fed into a game where they could ‘move objects with their mind’ by maintaining a concentrated state.

While the system we have set up works at a basic level, there is a lot of room for improvement to make the system more robust and effective. A few of the ways to improve on the system are by;

- Gathering more data
- Extracting more features
- Further research on useful / non useful features
- Multiple inputs into the game using blink detection, Event Related Potentials, Head movement etc.
- Implementing in other mediums such as Virtual Reality to offer a fully immersive experience

12.References

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