Analysis of Muse 2 EEG Data

Sofiia Petryshyn

Introduction

What is EEG?

An electroencephalogram (EEG) is a test used to evaluate the electrical activity in the brain. Brain cells communicate with each other through electrical impulses. An EEG can be used to help detect potential problems associated with this activity.
An EEG tracks and records brain wave patterns. Small flat metal discs called electrodes are attached to the scalp with wires. The electrodes analyze the electrical impulses in the brain and send signals to a computer that records the results.
The electrical impulses in an EEG recording look like wavy lines with peaks and valleys. These lines allow doctors to quickly assess whether there are abnormal patterns. Any irregularities may be a sign of seizures or other brain disorders.
In Figure 1 we can see the basic electrode placement of 22 electrodes on the right hand, and on the left hand, we can see EEG signal recorded.

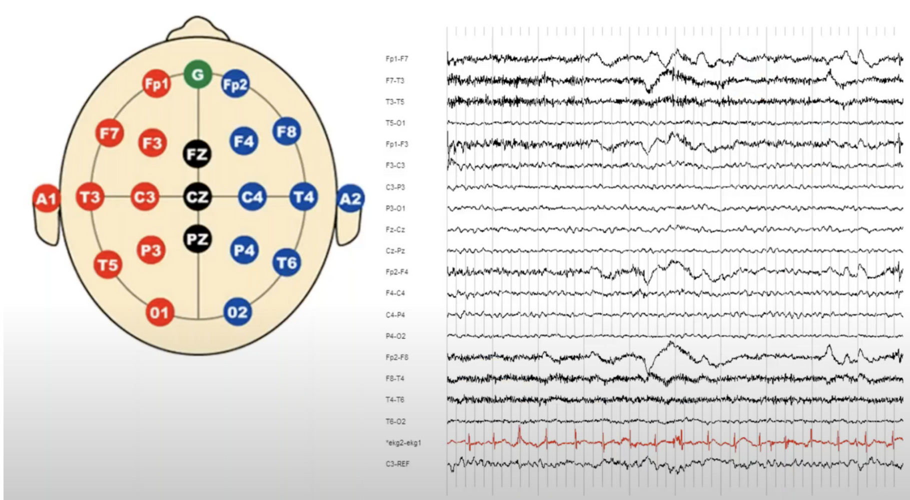

Fig. 1. Electrode placement

Why EEG?

An EEG signal is used to detect any activity that is happening in the human brain. Scientists can detect some brain disorders, emotions, or movements of particular parts of the body. The measurements given by an EEG are used to confirm or rule out various conditions.

Project idea and references

Dataset description

The first idea was to collect the dataset on my own using the Muse 2 device. However, I had some trouble collecting the data, as the device was discharging really fast while using it. However, I decided to use Muse 2 data collected by the other developer, Tim de Boer, from Amsterdam.
To collect the data from Muse I had to use third-party software called Mind Monitor, the app cost $15 and the signal recorded can be sent to the PC by Dropbox or by email. By pressing the record button, a CSV file is made. Data were collected at 256 Hz for the raw EEG signals, and 10 Hz for the brain wave data, accelerometer, gyroscope, Headband On or Off, HSI (Horse Shoe Indicator), and the marker button presses.
The setup was as follows (the following is copied from the paper):

1. The participant is sitting down on a chair with arms extended in parallel, resting on a table.
2. Two bottles of water are on the table. One of them is approximately 5 cm to the left of the left hand and the other bottle is 5 cm to the right of the right hand.
3. The participant's head faces forward, while the eyes rotate to the left, looking to the bottle.
4. We asked the participant to imagine picking up the bottle with the left hand, but without moving the hand; only thinking about it for 6 s.
5. Then, we asked the participant to look at the bottle on the right and imagine picking up the bottle with the right hand, but without moving the hand, only thinking about it for 6 s.
6. We repeated steps 4–5 for 3 times for each participant: 1 min in total.
7. Then, we repeated steps 1–6 for 5 times.

This resulted in 3 x 5 = 15 minutes of data. But because of zero values due to bad contact with the skin, there remained just 10 minutes of data. Using the brain wave data for all individual sensors, we have 4 x 5 = 20 features, which are the signal levels of the 5 different brain waves (gamma, beta, alpha, theta, delta), for each of the 4 sensors.
Important to notice, that the Muse device already filters the signal into the specific brain wave signals (gamma, beta, alpha, theta, delta) rather than raw EEG data.
The link to the database is provided here.
An example of data collected can be seen in Figure 2 below.

Fig 2. Example of EEG recorded.

Data pre-processing:

1. Step 1: outlier detection and removal with GMMs
2. Step 2: data transformation/feature engineering with PCA and ICA
3. Step 3: Temporal and Frequency Based Features

Related works:

1. Effective automated method for detection and suppression of muscle artefacts from single-channel EEG signal
   This paper involves three major steps: decomposition of the input EEG signal into two modes using VMD; detection of MAs based on zero crossings count thresholding in the second mode; retention of the first mode as MAs-free EEG signal only after detection of MAs in the second mode. The authors evaluate the robustness of the proposed method on a variety of EEG and EMG signals (EEG during mental arithmetic tasks database (EEGMAT)). Evaluation results using different objective performance metrics depict the

superiority of the proposed method as compared to existing methods while preserving the clinical features of the reconstructed EEG signal.

2. Outlier detection for single-trial EEG signal analysis
   The performance of a brain-computer interface (BCI) system is usually degraded due to the outliers in electroencephalography (EEG) samples. This paper presents a novel outlier detection method based on robust learning of Gaussian mixture models (GMMs). The proposed method was applied to the single-trial EEG classification task. After trial-pruning, feature extraction and classification are performed on the subset of training data, and experimental results demonstrate that the proposed method can successfully detect the outliers and therefore achieve more reliable results.

Sources:

1. https://www.mayoclinic.org/tests-procedures/eeg/about/pac-20393875#:~:text=An%20electroencephalogram%20(EEG)%20is%20a,lines%20on%20an%20EEG%20recording.
2. https://medium.com/building-a-bedroom-bci/collecting-brain-signal-data-using-the-muse-2-eeg-headset-a2d45ae00455
3. https://medium.com/building-a-bedroom-bci/pre-processing-of-muse-2-eeg-data-27666baeb631
4. https://ieeexplore.ieee.org/document/5910590
5. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7199290/