EEG Mental Activity Detector and Analyzer

Introduction

The existence of high-level cognitive behavior and consciousness was a puzzle that left humans dumbfounded and in awe for all of history until these past few decades. The field made crucial progress in the early to mid 20th century by moving the state-of-the-art observational method from introspection to various specialized neuroimaging techniques such as electroencephalography (EEG), computerized axial tomography (CAT/CT), positron emission tomography (PET), and magnetic resonance imaging (MRI). Despite these innovations, the field advanced relatively slowly due to the fact that (1) these imaging techniques required significant funding which made data collection inaccessible and (2) the degree of complexity of the problem is greater than likely any other scientific problem tackled. In order to solve for the latter point, researchers needed to recruit applied mathematics and machine learning methods.

In the past decade, two key developments that directly addressed these bottlenecks took place that unlocked the proliferation of knowledge and innovation in the field. First, the innovation and explosion of deep learning that took place nearly a decade ago paired with the steady increase in compute power accessibility gave way to mainstream adoption of powerful signal processing techniques. Secondly, commercialization of EEG devices has significantly lowered their price and allowed researches and developers to access this technology and generate the required data without significant funding.

Several companies have commercialized devices that monitor brain activity, infer general moods and activity, and offering the ability to control digital objects telekinetically. A large focus in the neurotechnology has been on monitoring and mitigating neurological diseases and injuries as well as supplanting damaged systems (in the case of paralysis).

Where previously powers of mind-reading, telepathic communication, and telekinesis only existed on the pages of comic books and blockbuster scripts, now all of a sudden these powers are a not-too-distant technological reality.

This project will explore the extent to which mental activities can be detected and classified using a 16 channel EEG headset. In the initial iteration of the project, the focus will be on very general, high-level activities such as listening, reading, and mental computation. Achieving accurate detection and classification of high-level ‘genres’ of thought will act as a first step for more complex inferences. As an example, a goal may be to build a device that will give the user the ability to communicate using brain activity. The first step in the development of such a device would be to prove that accurate classification of mental states such as listening, reading, and speaking are possible. Once that is achieved, the problem can be broken down into smaller and smaller subproblems, eventually creating modalities through which brain activity may be effectuated into communication or other physical activity.

Purpose

The goal of this project is to provide a proof of concept for the detection and classification of mental activities.The scope of this project is limited to the detection and classification of high-level mental activities, utilizing the global nature of EEG readings. (See the Glossary definition of ‘mental-activity’.)

Proposal

Data Collection

Hardware

The OpenBCI 16-channel EEG headset consisting of the daisy wired 16 channel Cyton board will be used. Data will be transmitted in realtime from the headset via RFDuino USB. The OpenBCI GUI will be used to receive and store the data [8].

16 channels will be distributed covering the following 10-20 regions:

10-20 Area	Macro-Anatomical Structure	General Function
Fp1	Superior Frontal Gyrus [6]	Attention [2]
Fp2	Superior Frontal Gyrus [6]	Judgment, Restraint of Impulses [2]
Cp5	Superior Temporal Gyrus [6]	Verbal Memory, Understanding, and Reasoning [2]
Fz	Superior Frontal Gyrus [6]	Working Memory [2]
Tp7	Middle Temporal Gyrus [6]	Auditory Processing, Verbal Understanding [2]
Tp8	Middle Temporal Gyrus [6]	Emotional Understanding, Motivation [2]
Fc5	Precentral Gyrus [6]	Verbal Expression, Motor Planning and Organization [2], [4]
Pz	Precuneus [6]	Cognitive Processing [2], [3]
F7	Inferior Frontal Gyrus [6]	Verbal Expression [2]
F8	Middle Frontal Gyrus [6]	Emotional Expression [2]
Af3	Superior Frontal Gyrus [6]	Between Motor Planning and Attention [2]

10-20 Area	Macro-Anatomical Structure	General Function
Af4	Superior Frontal Gyrus [6]	Between Motor Planning and Judgement Restraint [2]
T7	Middle Temporal Gyrus [6]	Verbal Memory [2]
T8	Middle Temporal Gyrus [6]	Emotional Memory [2]
P3	Inferior Parietal Lobule [6]	Cognitive processing — spacial temporal, verbal reasoning [2]
P4	Inferior Parietal Lobule [6]	Cognitive processing — spacial temporal, non-verbal reasoning [2]

Methodology

The headset will be worn during extended periods of various, prescribed mental activities, referred to as data collection “sessions”. For each of the mental activities, the subject will start the OpenBCI session just before beginning the mental activity, and end the session as soon as the activity session is completed. The first and last two minutes of each session will be cut from the data set since those timespans will likely contain many corrupting movement and mental artifacts. In general, until “focus” is achieved during each data collection session, the data is expected to be relatively noisy and will not match the label of the mental activity.

Each OpenBCI session should be labelled with the activity name and the data in the format: *activity_YYYY_MM_DD.*

The data collection effort will be conducted in phases, with each phase consisting of a set of mental activities that act as prerequisites for the detection and classification of the mental activities in the subsequent data collection phases. For example, Phase Zero, and the only non “mental activity” phase, will consist of “Artifacts,” unrelated physical movements that corrupt the data (see “Artifacts” in glossary for more). This will enable the development of a physical artifact detection model that will be used to clean the data generated in the subsequent phases of potentially corrupting physical artifacts.

<u>Phase Zero:</u>

- Blinking
- Jaw clenching
- Head shaking and nodding
- Frowning
- Smiling
- Contracting scalp muscles

<u>Phase One:</u>

- Silent Breath Meditation

  This activity will act as a baseline activity. The meditative state should, in theory, be distinguishable from all other mental activities listed since this meditation is mutually exclusive with all of the mental activities. If executed well, the practice of meditation focuses all mental activity on one objective thereby reducing overall noise. The objective of the meditation should not involve elements that overlap with the other mental activities. For example, a guided meditation would involve active listening.

  In order to prove that well-practiced meditation is a stand-in for heightened focus and thereby results in a reduction of overall noise, volatility over the course of the meditation sessions will have to be shown to be significantly lower than the volatility measured during the other mental activity sessions.

  To measure volatility, an alternative measure of variance was developed to account for the temporal context of observations rather than naïvely measuring against the mean of a group of observations as the standard measure for variance does. This will be used to track variance over time and can be a potentially robust measure of focus. See 'Development of the Volatility Metric Indicator' in the glossary for an in depth description of the volatility metric.

- Active Listening (classical music)
- Active Listening (podcast / talk show)
- Active Reading
- Mental Math Exercises

Proposed Signal Processing Pipeline

At each time step, the physical artifact detector inference result, the mental activity detector inference result, and, if relevant, all of the individual mental activity detector inference results will be returned.

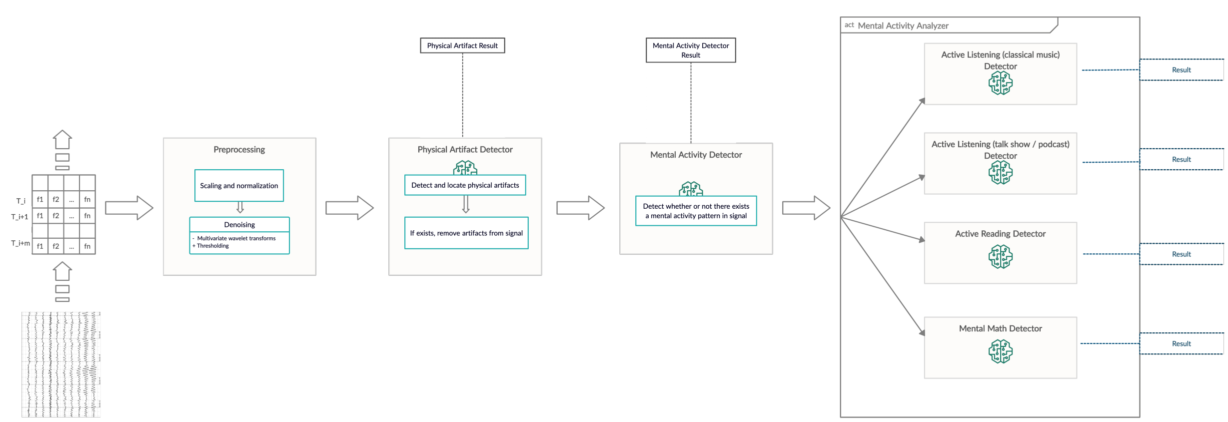

FIG. 1: DIAGRAM OF THE EEG MENTAL ACTIVITY DETECTOR AND ANALYZER PIPELINE

Preprocessing

Incoming data will be scaled using log transformations. This is due to the online nature of the problem — data cannot be normalized with respect to the *entire* feature set.

The signals will be de-noised using the multivariate wavelet method outlined by Aminghafari *et al.* so as to appropriately de-noise signals from each channel with respect to as opposed to in isolation from one another [1]:

1. Deconstruct the signals independently via discrete wavelet transform in order to generate the detail and approximation matrices.
2. Compute the covariance estimator of the initial detail matrix and perform singular value decomposition of the estimator to yield the orthogonal matrix *V*. *V* will be used as a change-of-basis matrix for the detail matrices.
3. For each detail matrix, apply the change of basis matrix *V* and cap values in the resulting matrix according to the thresholding strategy.
4. Apply the transpose of the change of basis matrix *V* to each detail matrix.
5. Reconstruct the signals via an inverse wavelet transform of the detail and approximation matrix.

The thresholding strategy will need to be tuned in tandem with the detector models.

Performing this multivariate wavelet transformation online may prove to be infeasible due to its complexity, however this will be used experimentally during offline learning. If the models that are developed in the subsequent steps of the pipeline are robust enough, then this de-noising step may not improve performance significantly.

Physical Artifact Detector

The primary purpose of the physical artifact detector is to clean the data of any corrupting artifacts prior to mental activity detection and classification. If an artifact is detected in the incoming signal, then the beginning and ending locations of the artifact will be identified and the signal will be smoothed over to represent a neutral signal prior to being routed to the mental activity detector.

Mental Activity Detector

The mental activity detector will act as the second filter for incoming signals, after the physical artifact detector. This detector will be trained to detect either the presence of, or the lack of an identifiable mental activity signal. Positively labeled data will consist of data aggregated from all mental activity sessions except for meditation. Negatively labeled data will consist of only data collection during the meditation sessions. Remember, in the scope of this project, meditation is synonymous with the lack of any mental activity.

Signals that are flagged as positive will then be routed to the mental activity analyzer.

Mental Activity Analyzer

The mental activity analyzer will be a set of detectors trained to identify each individual mental activity. The reason for this is so that the overarching classification can be optimized for precision and recall of each individual label. The positively labeled data will consist of data aggregated from the data collection sessions for that mental activity. Negatively labeled data will consist of data aggregated from all other data collection sessions. It will be assumed that all incoming signals were cleansed of any detected artifacts.

Model Architecture Proposals

Various natural language processing based model architectures will be explored for the detectors. Specifically, long short-term memory (LSTM) and attention based models will be explored due to their dominance in time series inference and prediction.

Model Benchmarking

Models will be trained to optimize for F1 score. See glossary for details.

Glossary

- 10-20 system
    - An internationally recognized system of placing electroencephalograph electrodes on the scalp. The 10 and 20 refer to the fact that the distance between neighboring electrodes are either 10% or 20% of the total arc length or width of the scalp. [6],[7]
- Artifact
    - A signal recorded by the EEG but not generated by the brain. These are usually due to scalp muscle movement or head motions.
- Attention based model
    - A technique for learning sequential relationships without defined sequence-length constraints. In traditional sequence based models, such as recurrent neural net's, a fixed input sequence length must be defined. Attention based models employs various attention mechanisms to learn global relationships between input and output sequences. See the original proposal for the Transformer model for more details. [10]
- Channel

- A stream of time series data generated by a single electrode.

- Development of the Volatility Metric Indicator
  - Let *M* denote the number of signals and *N* denote the number of timesteps in the given time window. Then, we can calculate the volatility across signals via the following formula:

$$\frac{1}{MN}\sum_{j=0}^{M}\sum_{i=1}^{N}(x_{i,j}-x_{i-1,j})^2$$

Calculating the variance by taking the difference between each time step and its subsequent timestep is preferred to classically calculating variance by taking the difference between each observation and the mean of the observations. This is because inter-timestep variance should be emphasized over total variance.

To illustrate the impact of this, consider the following case. For time window *A*, monotonically increasing perturbations of uniform size *d* are observed resulting in a group mean of *X.* For time window *B*, oscillating perturbations of size *2d centered at* X are observed. It can be shown that for all *N>3*, the observations from time window *A* result in a larger standard measure of variance than *B* even though the inter-timestep changes observed in *B* are double those observed in *A.*

- F1 Score
  - An accuracy measure often used especially when symmetry among class cannot be assumed. It is calculated by taking harmonic mean between precision and recall. A score of 1 indicates both perfect precision and recall while a score of 0 indicates either no recall or no precision.

- Long short-term memory, or LSTM
  - A gated recurrent neural net (RNN) architecture which aims to solve the exploding and vanishing gradient problem observed in vanilla RNN's during back propagation. An LSTM unit is usually composed of a series of gates that, produce an "internal error state" signal from new input as well as the signal from the previous unit. The internal error state signal is then propagated forward in time to the subsequent unit. [5]

- Mental Activity
  - A state of the mind that is focused on one particular objective. A high-level mental activity is a top-level objective categorization. These can be thought of as mental activity 'genre's'. A lower-level mental activity is on that exists as a sub category of another mental activity. Listing, reading, writing, speaking, and performing mental math are examples of high-level mental activities. Each of these mental activities can be sub-categorized: 'listening to music' is a sub category of the listening category, and 'listening to classical music' is a sub category of the 'listening to music' category, and so on.

- Precision
    - The true positive rate within the group of positively classified data.

$$tp/(tp + fp)$$

- Recall
    - The number of true positives over the sum of true positives and false negatives. In other words, of all member of the positive class, what percent was correctly classified.

$$tp/(tp + fn)$$

- Signal
    - Generically, data used as an indicator for some predictive output. A single data point can act as a signal if it has a direct correlation with the output. In the same vain, a collective set of points can act as a signal if the relationship among them indicates an output.
- Noise
    - Irrelevant, spurious, or otherwise unwanted variations in the data that reduce the overall predictive power of the data over the output. Noise and signal strength are measured relative to one another in a ratio. EEG, and brain signal data in general, have a very low signal-to-noise ratio meaning that noise is high relative to signal strength. [9]

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