HACKING THE BRAIN

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HOW THE ELECTRIC POTENTIALS IN OUR BRAIN CAN BE PROCESSED TO CONTROL A MACHINE

Introduction

A **Brain-Computer Interface (BCI)** is a system that uses voluntary neural activity (1) to control a computer. The neural signals created by a participant can operate an external device such as a pointer on the screen, video game or a prosthetic limb. The user is trained to generate conscious intention signals in the brain that the machine, also after undergoing training, translates into desired output commands(2). The purpose of this study was to use brain activity samples to develop a machine learning algorithm to control an external object.

1 Data acquisition

EEG signals were acquired non-invasively using **Ultracortex Mark IV** from participant1 (female,38) using a **notch filter of 60 Hz** to eliminate the influence of the electric line. For the purpose of this research, modified **Graz Motor-Imagery paradigm** was implemented. Each trial began with a crossbar on the screen, indicating no limb movement(t=0s). Then a left/ right arrow appears(t=3s) (representing the left/right limb motor imageries). The subject executes continuous motor-imagery until the arrow turns green (t=7s), indicating actual limb movement. Then the subject stays idle when the crossbar reappears(t=10s).

Figure 1

OPENBCI's **UltraCoretx Mark IV** is an open-source, 3-D printable headset that uses 16 dry electrodes, spatially distributed over the scalp in the 10-20 system of electrode placement, to acquire the oscillations of brain electric potentials. This headset is capable of recording research-grade brain activity

3 import Channel Locations

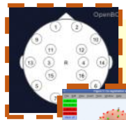

Figure 2

Figure 2

It is required to import the channel locations in EEGLAB for the specific equipment used to record the signals. For this research, the international 10-20 channel locations were imported. These locations need to be manually co-registered in order to wrap all the electrodes correctly around the scalp. This step is necessary before viewing 2-D and 3-D scalp maps or running ICA for accurate analysis.

5 Filter data

A digital filter attenuates a signal for each of its frequencies differentially. EEGLAB allows us to use numerous filters such as FIR, IIR, Butterworth IIR, Chebyshev IIR, Elliptic IIR, notch filters, etc. For our research, FIR filter was applied before ICA decomposition.

FIR (Finite Impulse Response) is a non-recursive filter that gives a stable output and is constant for all frequencies. However, it uses a lot of input to calculate the output and has a large delay(3). It is mostly used to remove slow, possibly large, amplitude drifts. For ICA decomposition, 0.5Hz-50Hz Band pass should be applied as ICA is sensitive to low frequencies.

IIR (Infinite Impulse Response) is recursive: it uses the current input sample together with previous output samples to calculate the current output sample. It is considered very efficient and has only a small delay. However, it can become unstable and can cause a shift in phase. The use of an IIR filter is appropriate when, a small absolute delay is required or when strong requirements on amplitude characteristic are necessary(3).

7 Plotting ERP and running ICA

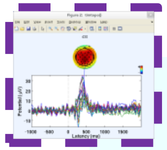

Figure 4

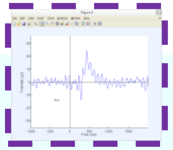

Figure 5

Event Related Potentials

ERPs are very small voltages generated in the brain structures in response to specific events or stimuli. We plotted ERP maps of single channel frequencies. This enables us to analyze the data in a much easier and visual way.

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Independent Component Analysis of EEG data

ICA is a machine learning algorithm that decomposes the brain signal into a set of components that are statistically independent. It allows to identify a difference in the patter of activation when the participant is thinking 'left' vs 'right'.

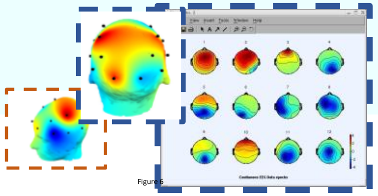

Figure 6

EEGLAB is a MATLAB toolbox used for storing, accessing, measuring, manipulating and visualizing different electrophysiological data such as EEG(4). It can be used to change the sampling rate (impulses recorded per second), to visualize an averaged or single-trial data in different ways, or to pre-process and apply required filters to the raw data.

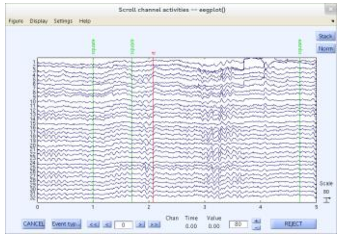

Figure 7

2 Import in EEGLAB

4 Re-referencing

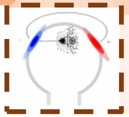

Figure 8

The flow of electric signals creates different dipoles in the brain. This accounts for some of the channel readings to be positive and others negative. So theoretically, sum of the electric field values recorded at evenly distributed electrodes around the scalp is always 0(5). Due to this nature of the brain waves, a reference needs to be chosen. Failing to do so may leave 40dB if unnecessary noise. Typical references in EEG recording is the TP10 mastoid in the 10-20 system, or some researchers use non-scalp references(earlobes, nose). However, no method is proven to be the best, so for the purpose of this experiment, we will be using an 'average reference'.

0	1	2	3	4	5	6	7	8	9	10	11	12
185	58618.86	53523.57	-30090.9	-35064.4	-23330.8	-8979.72	-20677.4	-5400.47	0	0	0	21:34:27.470
186	56983.38	53428.82	-31389	-35162.7	-23361.3	-8974.02	-20933	-5383.91	0	0	0	21:34:27.471
187	54007.64	53505.58	-34059.6	-36148.3	-23147.3	-8638.86	-22330.8	-5117.63	0	0	0	21:34:27.471
188	52158.42	53686.63	-35635.8	-36097.9	-22749.9	-8340.93	-22689.6	-4718.21	0	0	0	21:34:27.471
189	51213.07	53778.96	-36408.5	-35831.5	-22692.6	-8360.49	-22636.4	-4754.48	0	0	0	21:34:27.471

Figure 9

6 Manual Rejection of components

Rejecting bad channels : It is possible to have complete or partially flatlined channels in EEG data samples. This can be as an effect of the filters on specific frequencies or the change in the sampling rate of the data. It is necessary to remove these channels before running the ICA algorithm to get the best possible results.

before

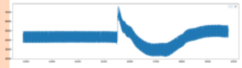

Figure 10

Removing spikes : Spikes can be easily identified in an EEG data. These spikes can be due to eye-blinks, muscle activities, or electronic fluctuations in the room. The best way to get rid of these spikes is to manually remove them.

after

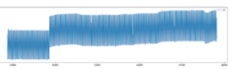

Figure 11

Discussion: Applications and future direction

Using machine learning and deep learning, this EEG data can be then used to make a brain-computer interface. The research community has developed BCIs with biomedical applications aiming at assisting users with movement or speaking disability. Some institutes around the globe have successfully engineered interfaces that help converting brain waves into words, and have even helped patients with the movement of a wheelchair solely operated with EEG. The next step of my research is to program a video game, operated by a BCI, to help patients with damage to the frontal cortex.

Figure 12

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