CE271 Final Project
Brain Waves

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0. Introduction

Neural oscillations, known as brain waves, have been most widely studied in neural activity generated by large groups of neurons. Large-scale activity can be measured by techniques such as EEG. In general, EEG signals have a broad spectral content similar to pink noise, but also reveal oscillatory activity in specific frequency bands. There are several different frequency bands each of which is assumed to be related to certain mental activities. Common frequency bands include alpha waves, beta waves and theta waves. This poster is comprised of two parts: blink detection and concentration detection.

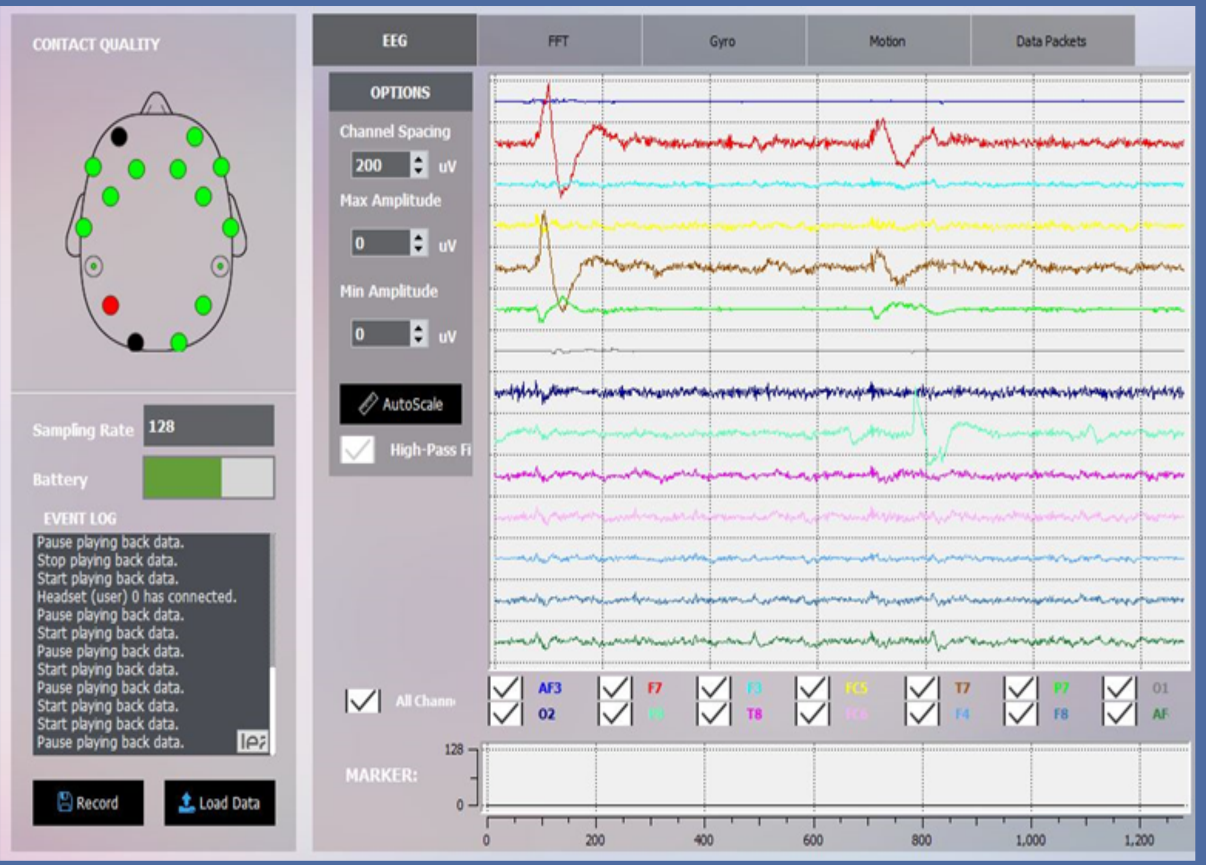
1. Blink Detection

1.1 Device

We use Emotiv headset to receive signals during the period of blinking. Emotiv is a 14 channel, high fidelity, wireless headset that monitors brain activity and translates EEG into meaningful data we can understand.

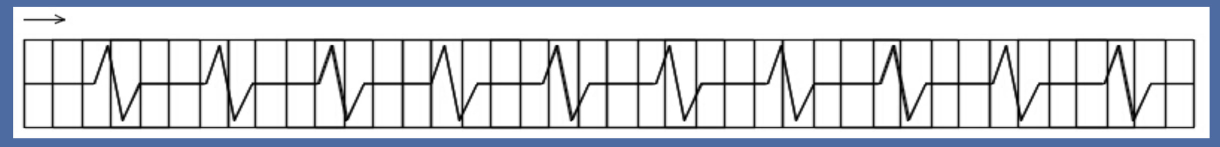
1.2 Raw data

By using Emotiv, we do tests on several targets to get the raw signal of blinking and winking. For each test, the subject blinks or winks every 5 seconds for 2 minutes, and data from all the 14 channels are collected.

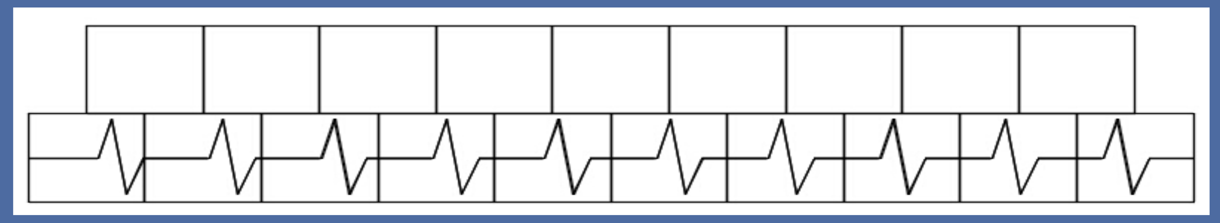


1.3 Slice Data

1.3.1 "Moving window" method

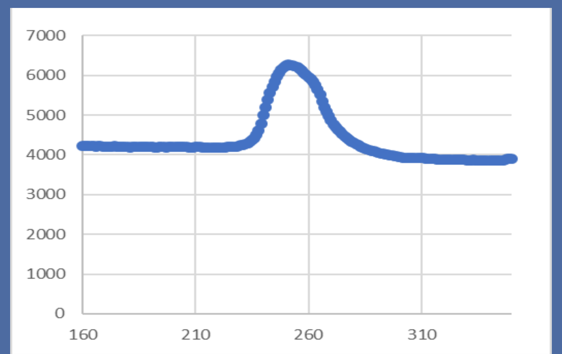


1.3.2 "Parallel boxes" method



1.4 Ideal Blink:

The ideal chunk is built using the "ensemble averaging" method. We first pick all chunks that contain a chunk, then normalize them by moving the centroid of the blink wave to the the middle of chunk. Finally, we can create ideal chunk by averaging all processed chunks.



1.5 Methodology

1.5.1 Features Extraction

- a) "dumb" approach: use all points as features
- b) PCA: pick the first two principal components
- c) t-SNE: embedded signal into 2 dimensions

1.5.2 k-means clustering

1.5.3 Pearson's coefficient method

$$r = r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}}$$

1.6 Result

We use confusion matrix to evaluate the detection results.

	Blink (detected)	Non-blink (detected)
Blink (actual)	True Positive (TP)	False Negative (FN)
Non-blink (actual)	False Positive (FP)	True Negative (TN)

Algorithm tested	False positives	False negatives
PCA	3	29
SNE	105	14.0
Threshold algorithm	16	10
Double channel PCA	1	28
Double channel Pearson's correlation coefficient	12	2

1.7 Conclusion

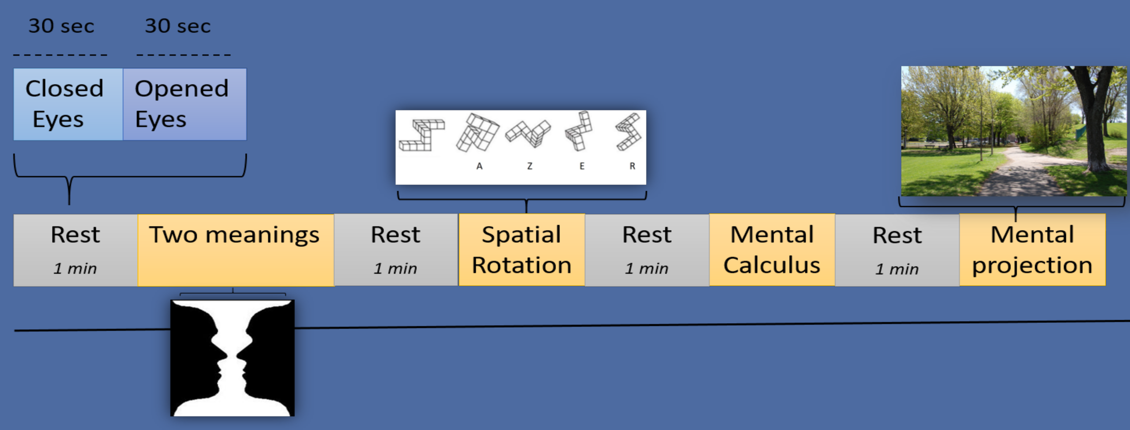
- a) Frontal channels are the more pertinent to spot blinks.
- b) Two Channels works better than one alone.
- c) Pearson's method is the best one for supervised learning.
- d) The homemade algorithm is the best one for unsupervised learning.

2. Concentration Detection

2.1 Experimental procedure

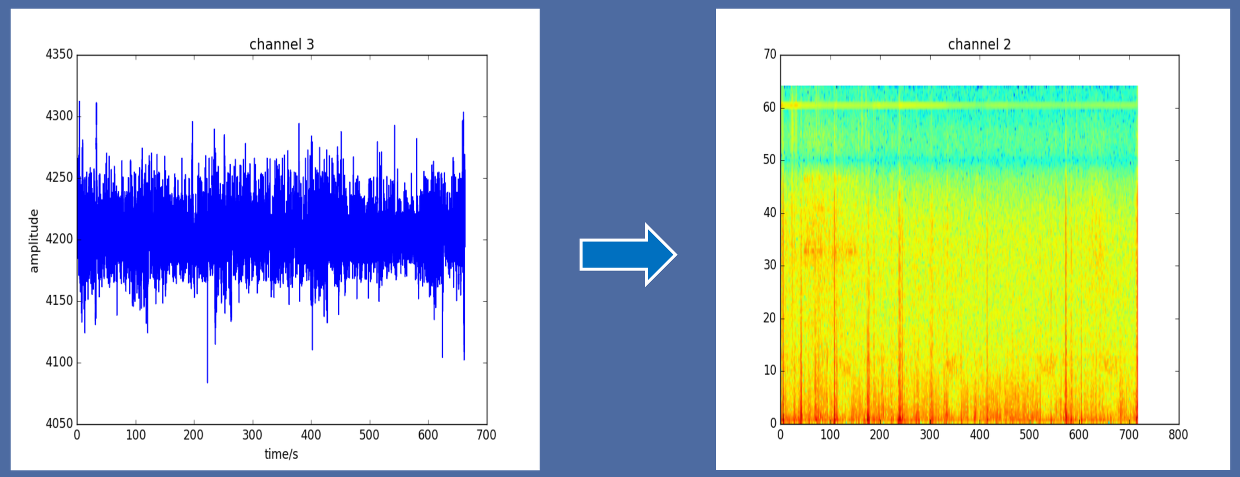
Subject: 6 students (2 females, age range from 22 to 24, M=23,16, SD=0,75, 2 left-handed) were recruited for the experiment with no diagnosed mental disorders. They have signed a consent but did not be compensated.

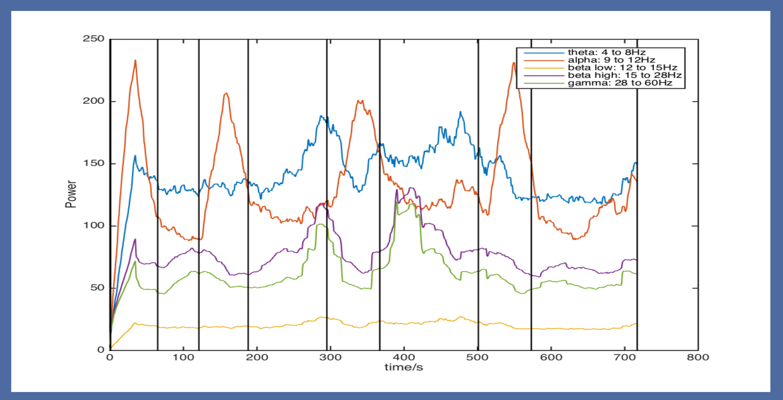
a) Two meanings: find 2 hidden meanings in 6 pictures
b) **Spatial rotation**: compare 6 sets of 3D objects and state if they are the same objects or if they are mirrored
c) **Mental calculus**: resolve 6 mental calculus
d) **Mental projection**: project themselves onto 4 sets of environment and imagine doing a corresponding action.



2.2 Result and analysis

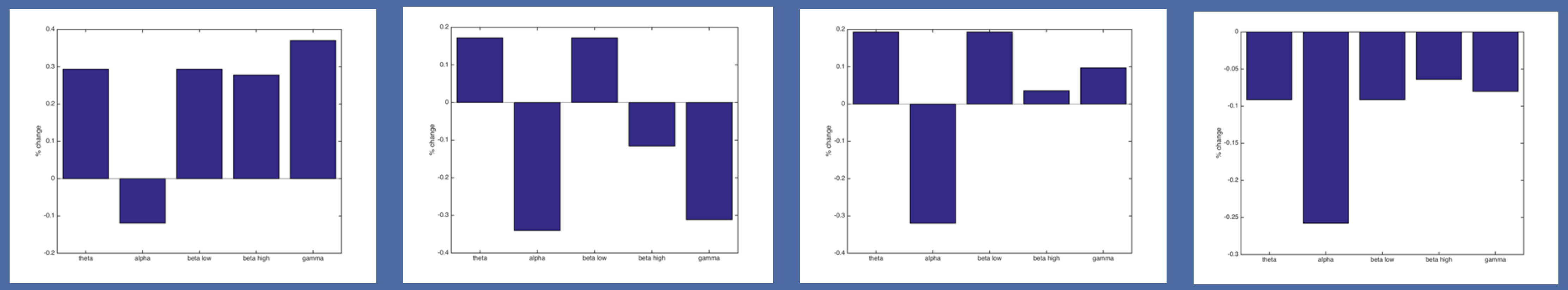
A typical time-domain signal over the entire experiment is shown as follows. It is obvious that no pattern can be extracted if we only focus on the time domain, thus we have to perform Fourier transform to get the frequency components of the signal. However, since the signal is not stable, we cannot perform Fourier transform over the entire time domain. An alternative would be using short-time Fourier transform. A good visualization of the short-time Fourier transform would be spectrogram. We plot the spectrograms for all the subjects on channel 2 (fore head).





An immediate observation is that during all the periods when eyes are closed, the power of alpha wave (8 to 12 Hz) increases a lot and decreases when eyes are open. This agrees with most of the research results. To further explore that, we plot the average power of each brain waves over time (θ wave: 4 to 8 Hz, α wave: 9 to 12 Hz, low β wave: 12 to 15 Hz, high β wave: 15 to 28 Hz, γ wave: over 28 Hz). And we used a MA filter to smooth the data.

In order to find the behavior of all the other waves when the subject is concentrating, we calculate the change rate of power of each wave when the subject begins concentrating. We take the mean value V_r of each wave during the resting period and the mean value V_c during the concentration period, and calculate the change in terms of percentage, $\frac{V_c - V_r}{V_r}$. We calculate this change rate for each task for each subject, and for each task, we average the change rate over all the valid task.



2.3 Conclusion

Alpha wave is related to eye closing. When people close his/her eyes, the intensity of alpha wave increases and when people open his/her eyes, it decreases. The theta wave and low beta wave is related to concentration. Their intensities increase when people are in concentration.