Brain Signal Biometrics with Virtual Reality

Team Members

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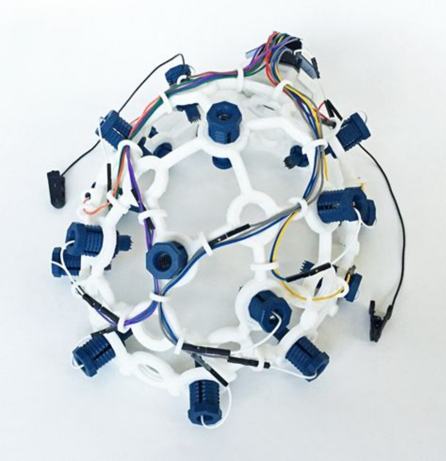
Introduction:

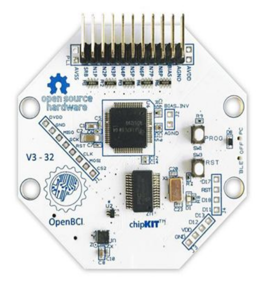
- The overall goal of this study is to determine whether the presence of Virtual Reality (VR) affects brain signaling as measured with an electroencephalogram (EEG) and if those brain signals can be used for user authentication
- A Brain-Computer Interface (BCI) is used to capture EEG brain signals in an attempt to understand how our brains are working during VR and non-VR stimuli
- There has been limited research in Human-Computer Interaction (HCI) about how VR affects brain activity

Hardware

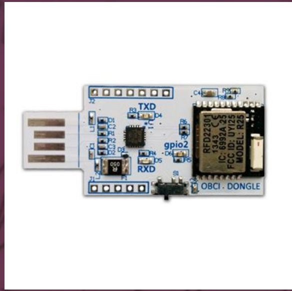


Ultracortex “Mark IV”
EEG Headset

OpenBCI 8-channel
“Cyton” board



OpenBCI USB
dongle



Dry EEG Comb
Electrodes

VeeR VR Cardboard

Hardware - changes

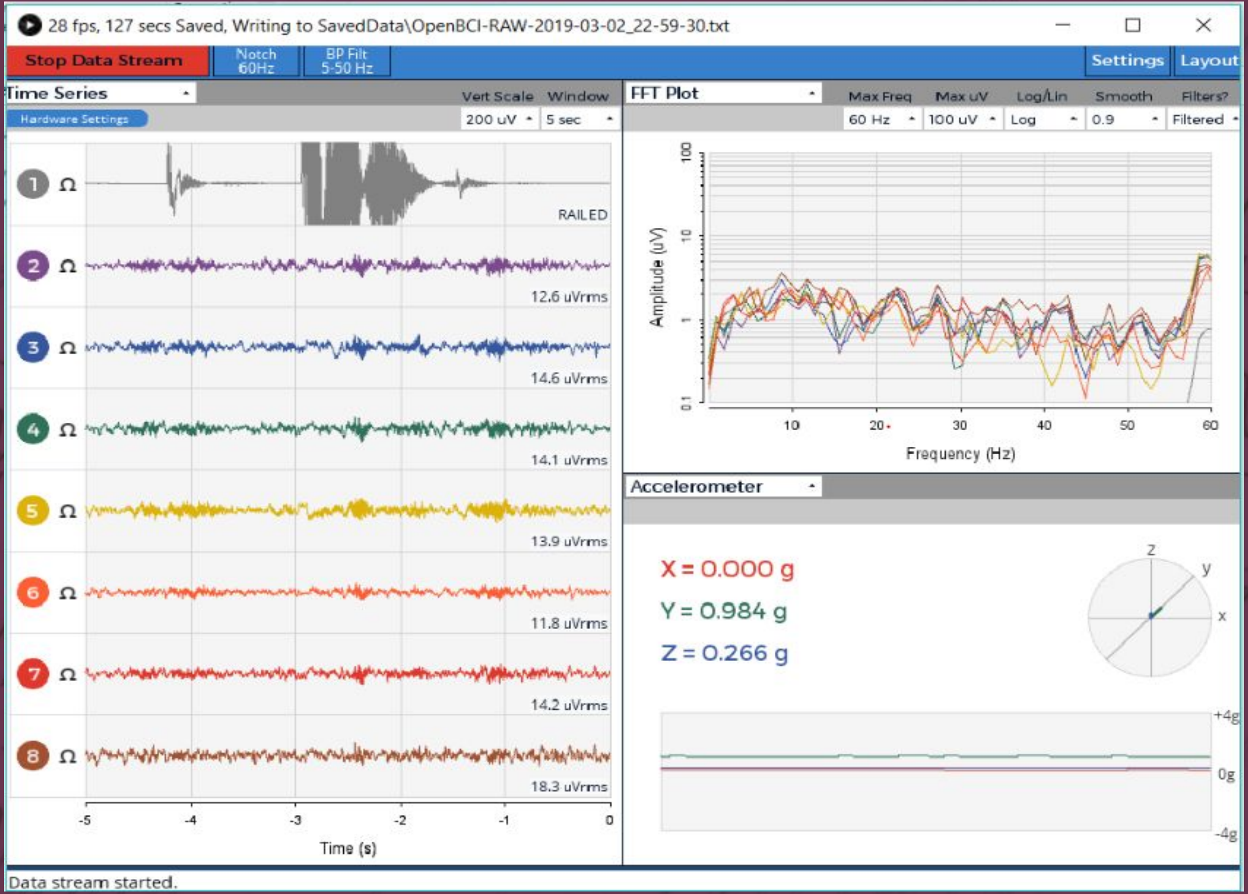
- The change to 5mm Comb Electrodes helped improve data collection greatly
- Not only are the longer spikes better at reading brain signals on long-haired participants, the rounder tips provide greater comfort

Old Electrodes

New Electrodes

Software/Libraries

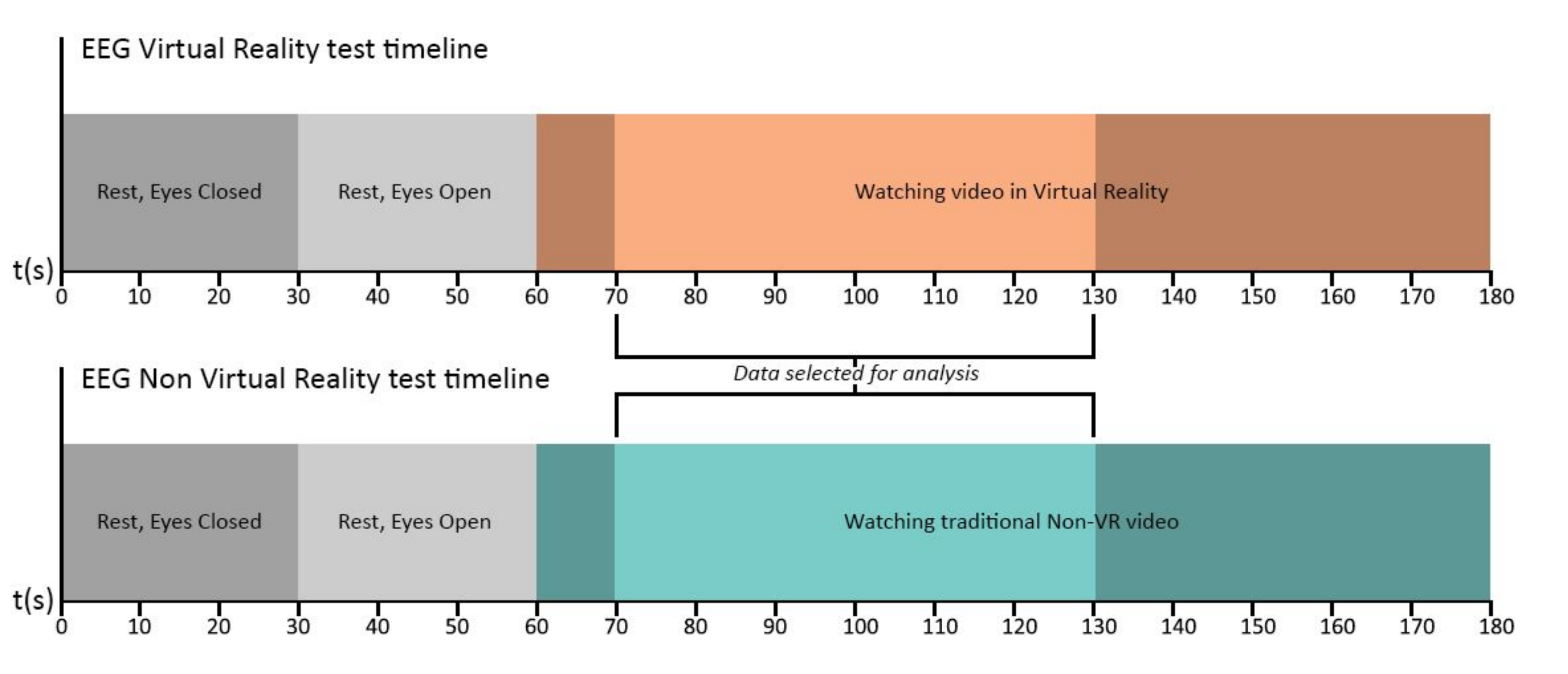
- OpenBCI GUI
- MNE Python
- NumPy
- Pandas
- Matplotlib



Experiment Procedure – Data Collection

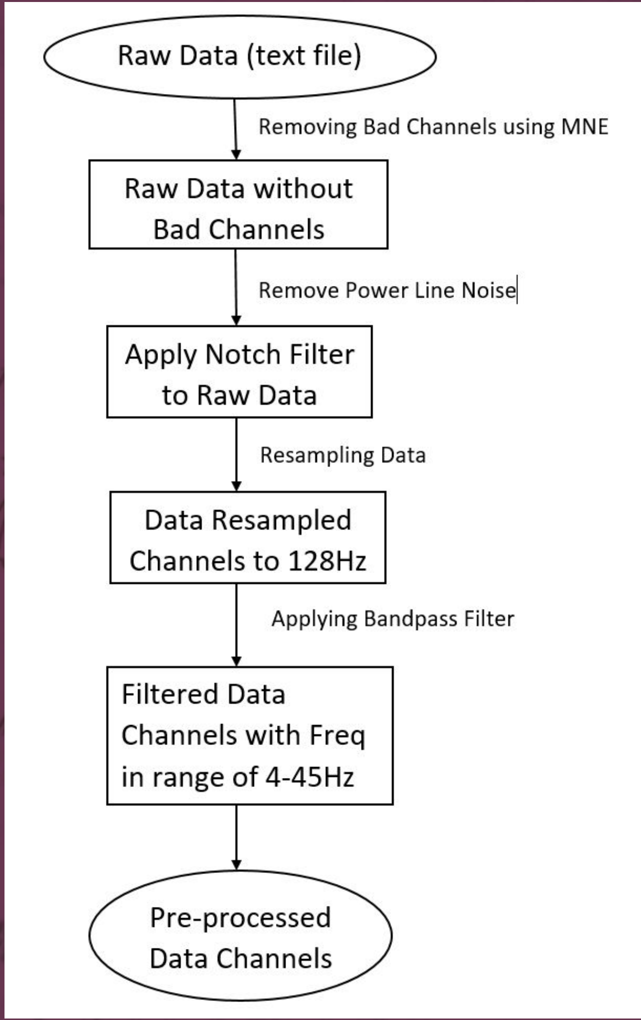
- EEG data was collected for an additional 16 subjects
- Each test is 3 minutes in length
- The first 60 seconds are a resting phase (30s eyes closed, 30s eyes open)
- For the remaining 2 minutes the participant watches a video
- First test is with a VR video, the second test is the same video watched on a traditional monitor (NonVR)

Two Sessions of Experimentation



Pre-Processing

- Before any analysis can take place the collected data must first be pre-processed to isolate any “bad channels” and remove background noise
- The pre-processing software used is a custom workflow built during last semester’s research for the specific needs of this project



Analysis

- Three methods were chosen for feature extraction:
  - Statistical Histogram (SH)
  - Auto-Regressive (AR)
  - Power Spectral Density (PSD)

- For consistency only Ch.4 from 70s to 130s was chosen for analysis

- This ensures that the same relative data is being analyzed for each subject

- Data was then divided into 5 second segments for feature extraction

Feature Extraction - Statistical Histogram (SH)

- Statistical representation of frequency distributions for a signal during a time series

- Chosen features: mean, median, standard deviation, z-score, skewness, kurtosis

Feature Extraction - Autoregression (AR)

- Time series analysis based on time steps as input

- The AR model predicts future value of y_i based on past values y_{t-1}

Feature Extraction - Power Spectral Density (PSD)

- Output is the ratio of its power content versus its frequency

- Used Welch's method with 128 sample frequency and 2 second window size

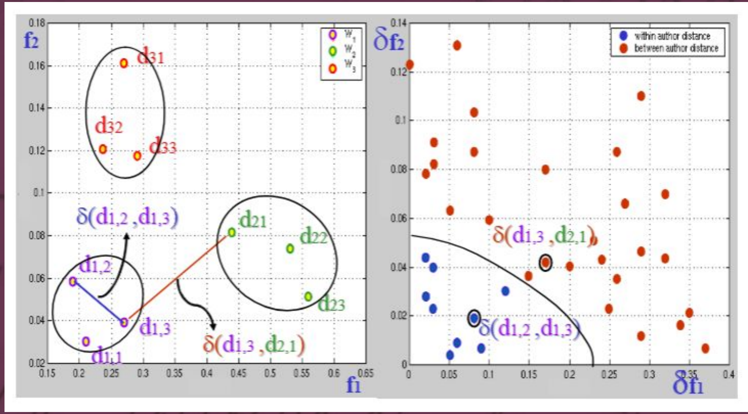
- This method divides the time signal into segments, takes the periodogram for each, and averages them

Feature Analysis - Dichotomizer

- For each pair of datapoints, the 'absolute distance' for each feature is calculated

- Intra distance pairs (same subject) are marked as class 0 and inter distance pairs (different subjects) are marked as class 1

- This 'feature distance domain' is what gets used to train the Support Vector Machine



Classification - Support Vector Machine (SVM)

- We chose to train the SVM with an equal proportion of class 0 (intra) and class 1 (inter) data

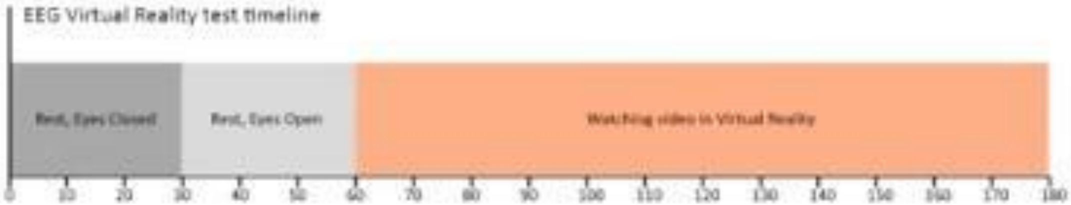
- We used a Radial Basis Function (RBF) kernel and a 70/30 train/test split

- Preliminary findings gave very low results for AR (10%) and PSD (12%). Our solution to this was to apply a second round of feature extraction on these models, combining the Statistical Histogram with the output from AR and PSD

- Results from the combined methods were significantly better

Classification Results

Method Name		Accuracy Rate	False Acceptance Rate	False Rejection Rate
Statistical Histogram	NonVR	75.08%	12.54%	12.36%
	VR	71.66%	11.31%	17.01%
Autoregressive with Statistical Histogram	NonVR	75.70%	15.03%	09.25%
	VR	75.62%	14.73%	10.00%
Power Spectral Density with Statistical Histogram	NonVR	70.92%	16.57%	12.50%
	VR	70.92%	13.98%	15.09%


EEG Virtual Reality test timeline
Rest, Eyes Closed
Rest, Eyes Open
Watching video in Virtual Reality
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180

Conclusions

- While we found no significant benefits to classifying VR vs NonVR data we also found no drawbacks.

- Our highest results were from the AR+SH method and both the AR+SH and PSD+SH had very consistent results. Which suggests that this combined feature extraction approach has a lot of benefits over single feature extraction methods.

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Future Work

- We’re proud of our results but feel there’s still room for improvement in accuracy scores

- Some things to consider:
    - Increasing the dataset by collecting data from more subjects
    - Expanding the feature extraction step to include more features
    - Trying other types of classifiers
    - Increasing the number of channels used in the data analysis

Thank You!