Electroencephalogram (EEG) Classification

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Background

*An electroencephalogram (**EEG**) is a test that detects electrical activity in your brain using small, flat metal discs (electrodes) attached to your scalp. Your brain cells communicate via electrical impulses and are active all the time, even when you're asleep. This activity shows up as wavy lines on an **EEG** recording. [Mayo Clinic]*

The goal of this project was to classify brain states from EEG data. A joint CU Anschutz/ ULN project has collected EEG data on subjects during sessions in which the subjects were instructed to visualize performing a motor-based task.

Each subject performed one session visualizing a very familiar task, and another session visualizing an unfamiliar task.

Objectives

- *The primary goal was to develop a classifier that can correctly identify whether a subject is visualizing a task that is familiar or unfamiliar.*
- *Secondary goals included providing insight into which brain regions and frequency bands associate with each of the respective classes. If a deep learning approach is found to be viable, these insights may correspond to latent features found within the neural network.*
- *Other insights may be obtained from more traditional data processing and machine learning techniques.*

Approach

Relying on previous EEG research done by Beshivan et. al.[1], as well as the latest advances in video classification[3], the approach was to process the 14-channel time-series data into discreet one-second 'frames' and project these frames onto a 2D map of the surface of the head. Then a convolutional neural network (CNN) was trained to classify frames.

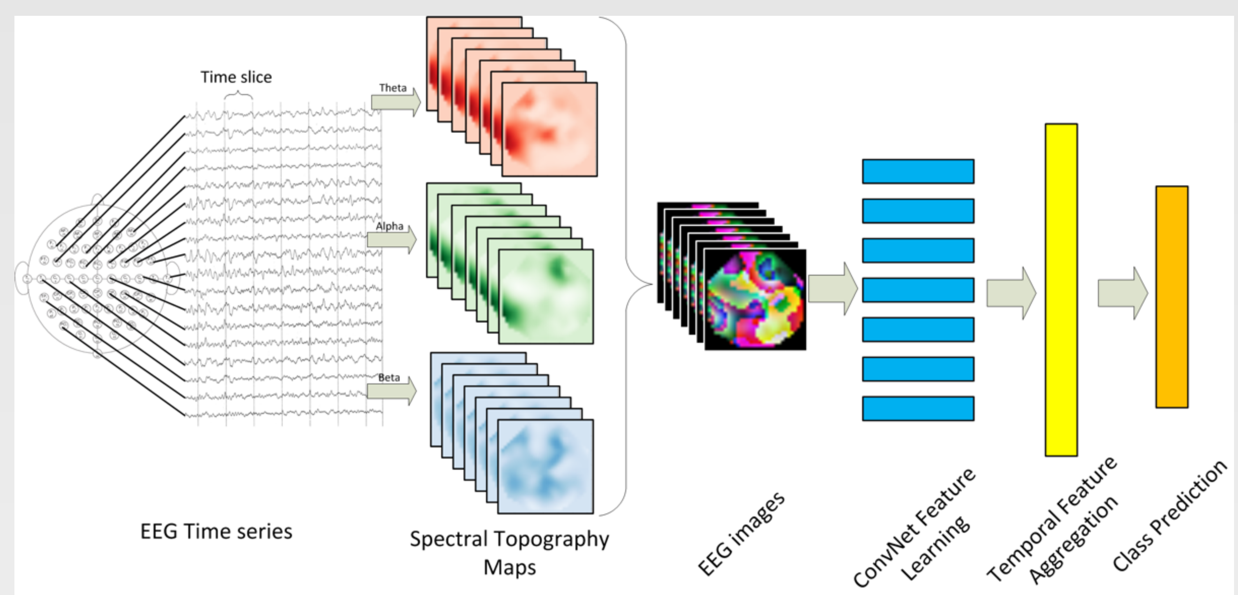

Figure 1:EEG classification architecture proposed by [1].

The Data

The data are in the form of csv files with raw waveform signals from 14 probes places around the scalp. The sampling rate is 128 hz, which allows for frequency analysis up to ~60 hz. Each of 8 subjects participated in two minute-long sessions.

The image below shows the raw waveform data from four of the 14 channels during a typical session. EMG signals (such as those causes by swallowing or yawning) were manually removed.

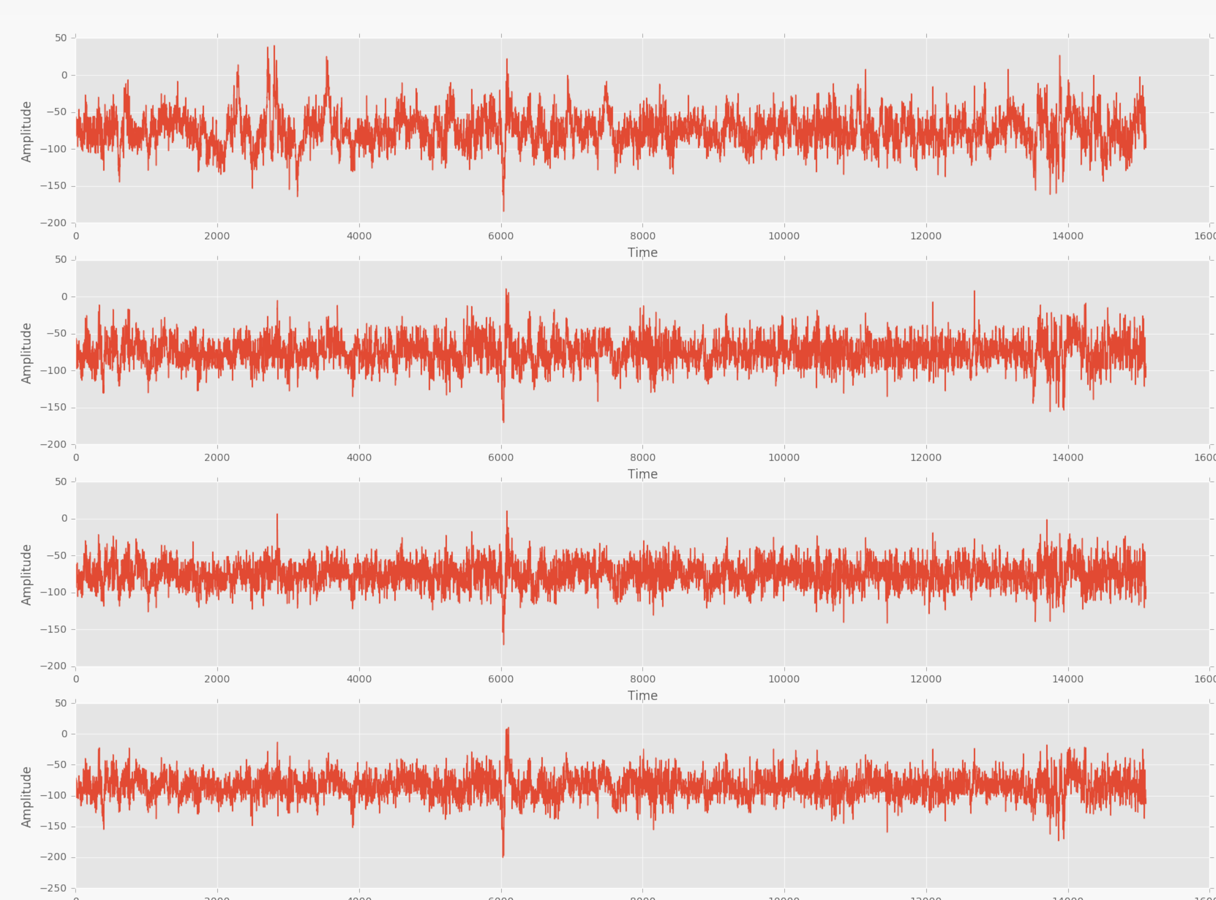

Figure 2: Raw waveform data from four of the 14 EEG probes

Data Processing

***Hanning Window:** First the data were chopped up into overlapping 1-second 'frames' and a Hanning window was applied.*

***Fast Fourier Transform(FFT):** FFT was applied to transform data for each frame from time domain to frequency domain.*

***Frequency Binning:** FFT amplitudes were grouped into theta(4-8Hz), alpha(8-12Hz), and beta(12-40Hz) ranges, giving 3 scalar values for each probe per frame.*

***2D Azimuthal Projection:** These 3 values were interpreted as RGB color channels and projected onto a 2D map of the head.*

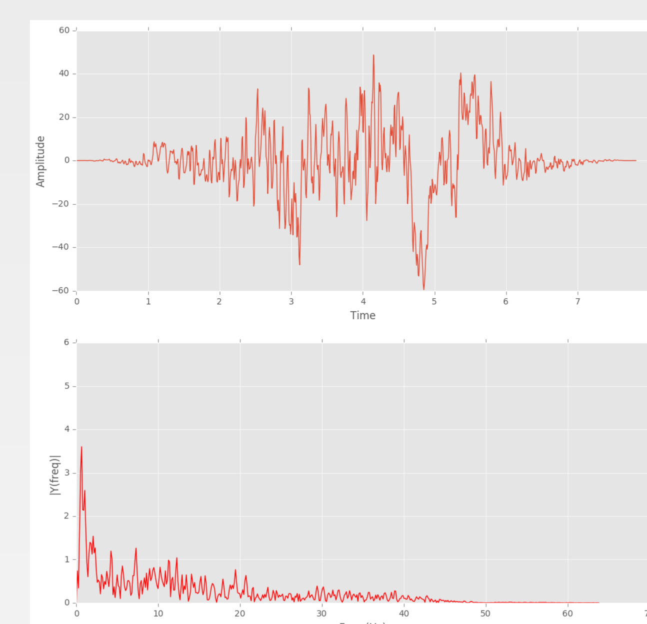

Figure 3: Hanning windowed one-second frame and FFT.

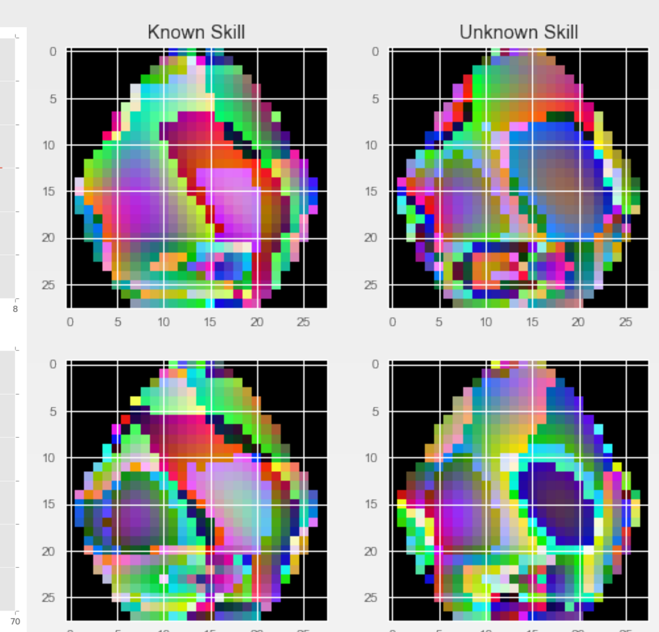

Figure 4: 2D projections of theta, alpha and beta ranges.

Results

- ***85% validation accuracy when the CNN had been trained on data from the same EEG session.***
- ***81% validation accuracy when then CNN was trained on all individuals but had never seen the test session.***
- ***71% validation accuracy when the CNN had been trained on all data from other individuals but had never seen the test individual.***

Discussion

The results obtained are encouraging. Without even using a recurrent neural network (which is the next logical step, see [1]), the CNN is able to correctly classify the test subject's brain-state about 8.5 times out of 10. This is likely high enough to enable a new level of performance with brain-computer interface (BCI) technologies.

However, the best results were obtained when the network was trained on samples from the same recording session. While this may be practical for basic brain research, it would be less practical for use in BCI technology.

The results obtained suggest that while EEG signals do indeed generalize between individuals, there are still significant variations between individuals, which is an unsurprising finding.

This further suggests that using EEG for BCI will likely require an iterative approach of training on a large population and then fine tuning on a specific individual. It is therefore recommended that future research be done on the possible application of Transfer Learning techniques to the classification of EEG signals.

References

[1] Learning Representations from EEG with Deep Recurrent-Convolutional Neural Networks
19 Nov 2015. Bashivan et al. Cornell University Library.

[2] A novel deep learning approach for classification of EEG motor imagery signals
30 Nov 2016. Tabar and Halici. IOP Publishing.

[3] Beyond Short Snippets: Deep Networks for Video Classification
13 Apr 2015. Ng et al. Cornell University Library.