Decoding EEG Waves for Visual Attention to Faces and Scenes

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Introduction

Background:

The incorporation of Brain Computer Interface (BCI) systems into fields such as healthcare, education, and entertainment has been an area of interest across many academic circles in recent years. This platform of BCI decodes brainwave patterns during a sustained period of visual attention to a specified task. During a period of visual attention, electric potentials are created in response to synaptic activity across neurons. These potentials were collected as signals through the non-invasive technique of scalp ElectroEncephaloGrams (EEG).

Objective:

The goal of this project was to improve the prediction accuracy for a EEG signals using a deep neural network and signal processing techniques.

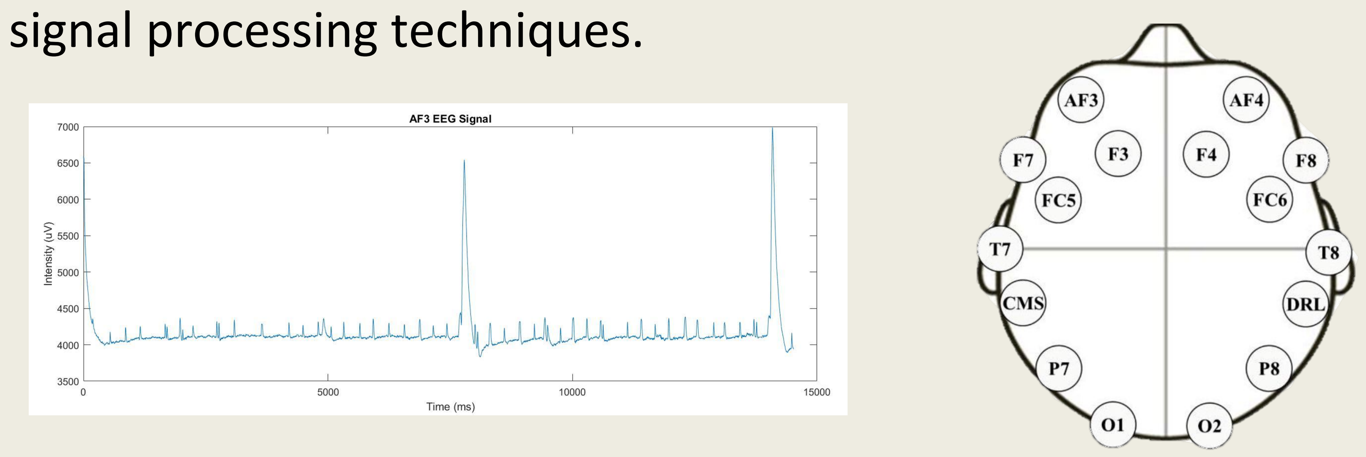

Figure 1: Raw EEG Signal and Channel Layout

Data Collection

- Data from 2 subjects was collected across 14 channels using the Emotiv Headset
- Each Subject produced 400 Image Trials containing signal data that was analyzed and processed within the model
- Sub-Categories were used to ensure the participants gave visual attention to the category assigned

Block Number	Task-Relevant Image	Task-Irrelevant Image
1	Indoor	Outdoor
2	Male	Female
3	Indoor	Outdoor
4	Female	Male
5	Outdoor	Indoor
6	Male	Female
7	Outdoor	Indoor
8	Female	Male

Figure 2: Image Trial Sub-Category Breakdown

Model

Pre-Processing and Feature Extraction:

- Raw EEG signals were filtered in the frequency domain to remove artifacts that distort the signal prior to feature extraction
- Features were extracted in 56 frequency bands with a range of 1 Hz

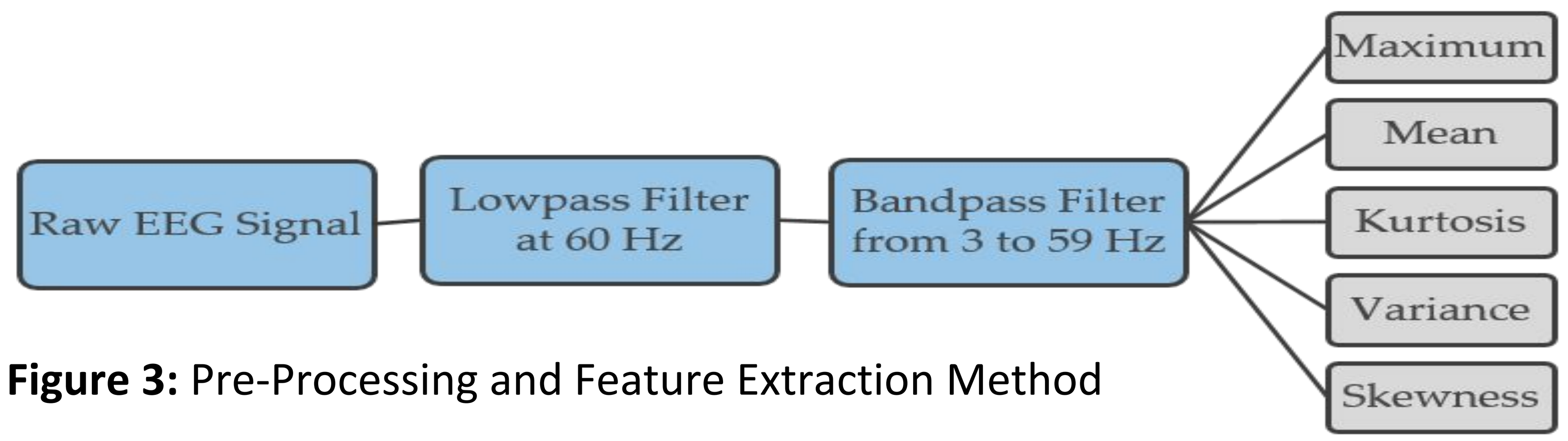

Figure 3: Pre-Processing and Feature Extraction Method

Data Augmentation:

- Split and combination method was applied to increase the number of training examples (Figure 4)
- EEG signals were cut and randomly combined to produce 1600 training examples

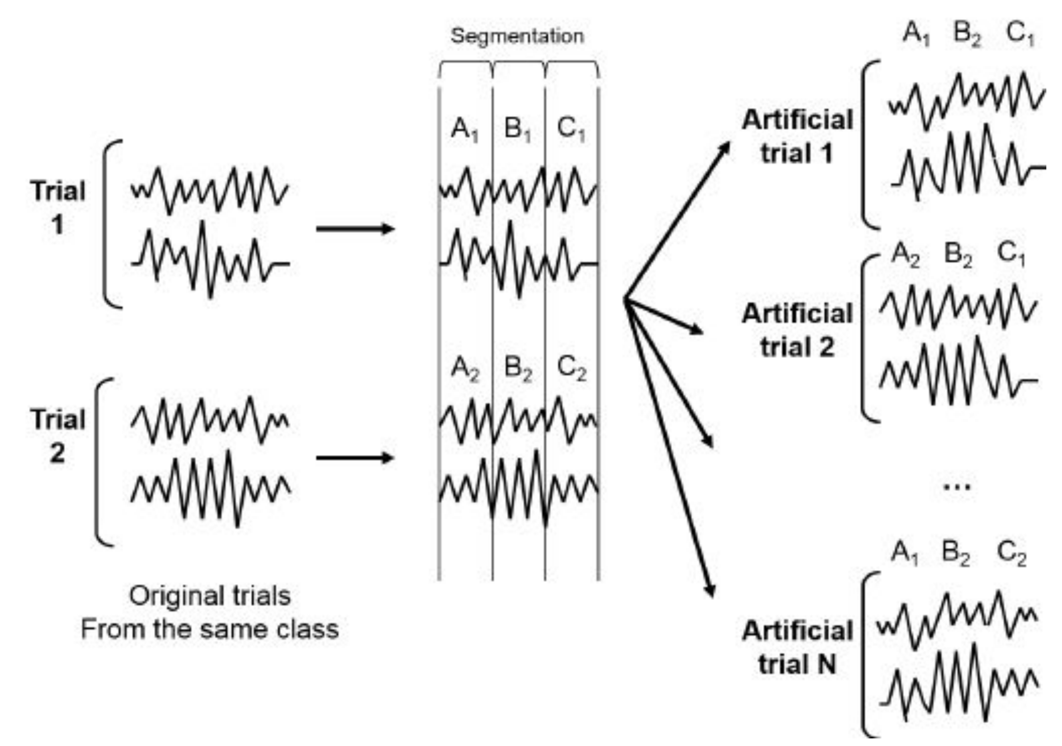

Figure 4: Split-and-Combination Method[1]

Cross Validation and Random Seed:

- 10-Fold cross validation was used with a training-to-testing ratio of 0.9 (Figure 5)
- Random seeding was used to ensure reproducible results

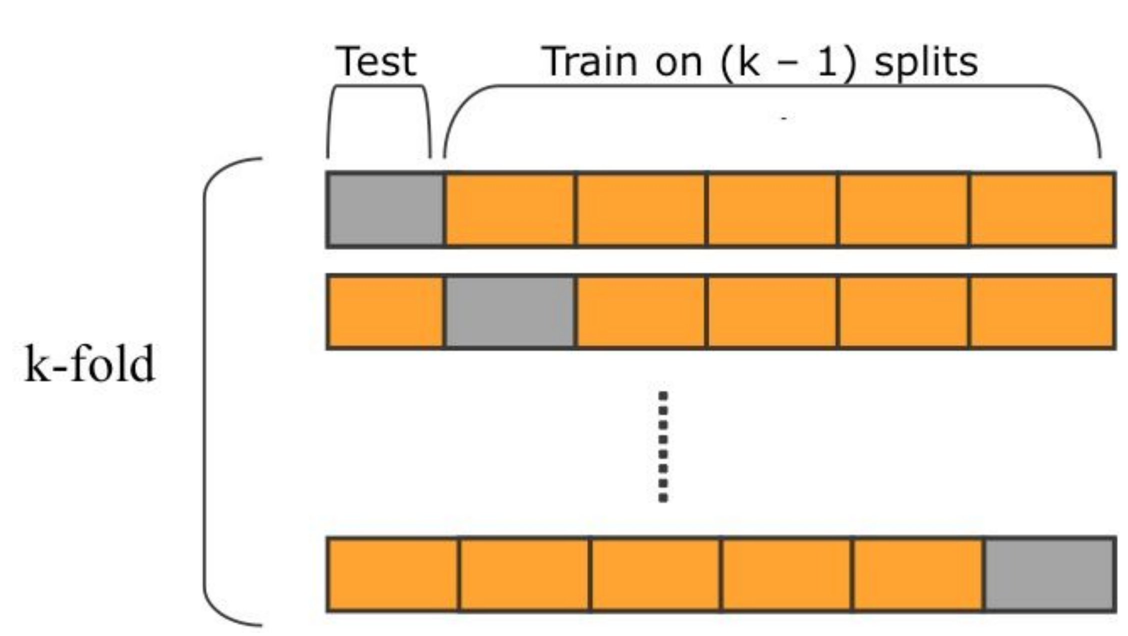

Figure 5: K-Fold Cross Validation Method[2]

Convolutional Neural Network

Model Dimensions:

- 2D and 3D Convolutional Neural Networks (CNN) were compared and 3D models proved to be more efficient for our data type
- Each Image Trial dataset was reshaped to a 28*28 matrix

Model Layer Structure:

Layer	1 CONV3D	2 CONV3D	3 CONV3D	4 FC	5 FC
Filter	(3,3,3) #1 = 6	(2,2,2) #2 = 12	(3,3,3) #3 = 24	56	1
Activation	relu	relu	relu	relu	sigmiod
Pooling	NA	(2,2,2)	(2,2,2)	NA	NA
Loss: binary_crossentropy			Optimizor: Adam		

Results

- The number of epochs and model parameters such as early stopping was tested and evaluated using the average and standard deviation of the testing accuracy across 10 folds
- Below are the best model parameters after current testing

3D CNN with Early Stopping (Patience = 10)	Mean (std) = 74.38% (3.61%)
	Max = 80.62 MIn = 66.88
3D CNN (Epoch = 50)	Mean (std) = 74.56% (5.18%)
	Max = 84.38 MIn = 67.5

Future Work

Pre-Processing:

- Test Continuous Wavelet Transform (CWT)
- Optimize number of frequency bands on model accuracy

Model:

- Optimize Dropout Rate and Optimizor function
- Optimize CONV3D layers

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References

[1] Lotte, F. (2015). Signal Processing Approaches to Minimize or Suppress calibration Time in Oscillatory Activity-Based Brain-Computer Interfaces. *Proceedings of IEEE,* 103(6). 871-890
[2] Kong, Q. (2017, February 12). Machine Learning 9 - More on Artificial Neural Networks. Retrieved from http://qingkaikong.blogspot.com/2017/02/machine-learning-9-more-one-artificial.html