Decoding EEG Waves for Visual Attention to Faces and Scenes

Taylor Berger and Chen Yi Yao

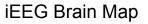




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Brain Computer Interface

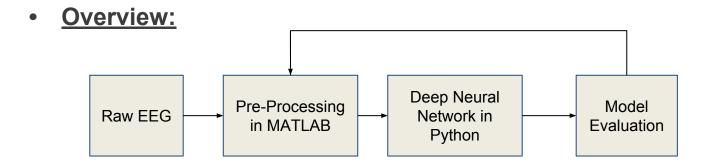
- <u>Applications:</u>
 - Medical Devices (e.g. Prosthetics, Wheelchairs)
 - Educational and Self-regulation
 - Games and Entertainment
 - Security and Authentication
- Invasive vs. Non-Invasive:
 - Intracranial ElectroEncephaloGraphy (iEEG)
 - ElectroEncephaloGraphy (EEG)





Research Objective and Overview

• **Objective:** Develop a filtering technique and a neural network model to improve the test accuracy of the system based on extracted information from EEG signals



Data Collection

- Emotiv EPOC Headset: 14 Channels
- 38 Subjects
- **Phase 1:** Distinction between image subcategories
- 8 Blocks (50 image trials / block)

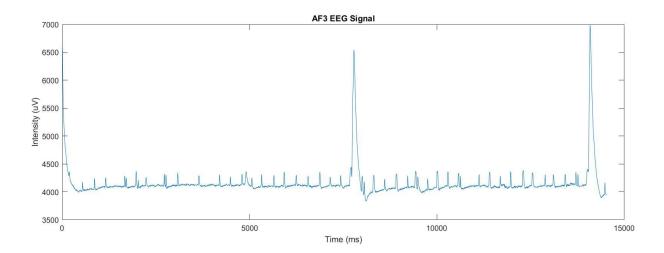
Emotiv Headset



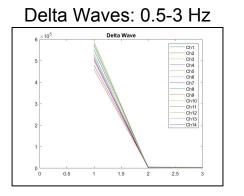
Block Number	Task-Relevant Image	Task-Irrelevant Image	
1	Indoor	Outdoor	—— Scene
2	Male	Female	
3	Indoor	Outdoor	
4	Female	Male -	— Face
5	Outdoor	utdoor Indoor	
6	Male	Female	
7	Outdoor	Indoor	
8	Female	Male	

Noise

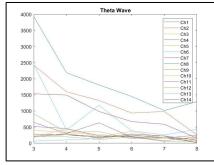
- Inherent electrical properties and physical arrangement of tissues
- Muscle Twitches
- Eye Blinks



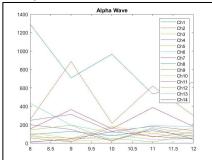
Brain Wave Frequencies



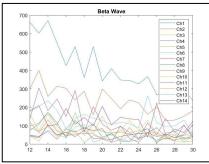
Theta Waves: 3-8 Hz



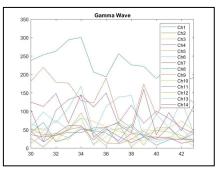




Beta Waves: 12-30 Hz



Gamma Waves: >30 Hz



Pre-Processing Methods

- Low-Pass Filtering
 - Baseline Testing
- Band-Pass Filtering
 - Feature Extraction
- Continuous Wavelet Transform
 - Feature Extraction
 - Image Representation

Low-Pass Filter

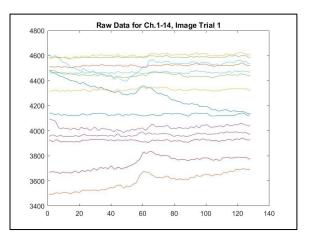
• Passes signals below a cutoff frequency and attenuates signals above

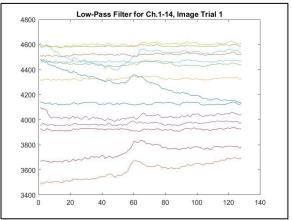
Inputs:

Cut Off Frequency: 40 400 x [14x128]

Outputs:

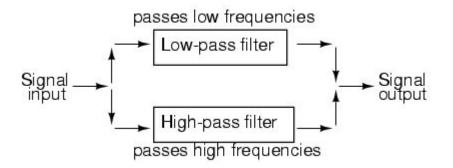
400 x [14x128]





Band-Pass Filter

- Passes signal through a frequency window and attenuates frequencies outside of a specified range
- Able to specify frequency ranges applicable to attention



Band-Pass Filter

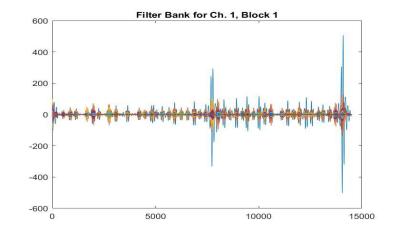
 Broken into 56 frequency ranges between 3 and 59 Hz for each Image Trial

Input:

400 x [14x128]

Output:

400 x [14x128x56]

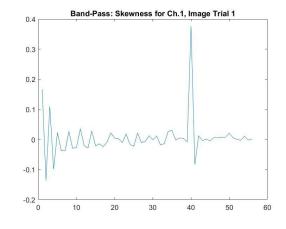


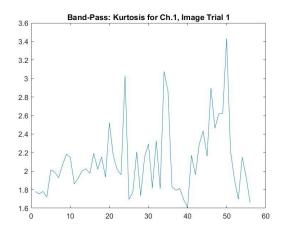
Band-Pass Feature Extraction

Statistical Parameters

- Mean
- Maximum
- Kurtosis
- Variance
- Skewness

Input:





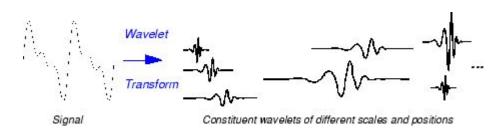
400 x [14x128x56]

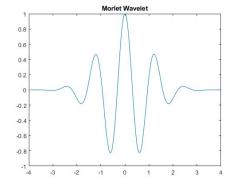
Output:

400 x [14x56x5]

Continuous Wavelet Transform

- Measures the similarity between a signal and an analyzing function
 - Analytic Morlet Wavelet
- Compares the signal to shifted and compressed or stretched versions of the wavelet





CWT Filter - Approach 1

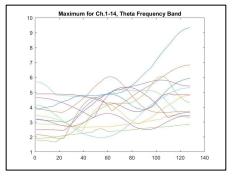
- Divided the decomposed signals into 4 frequency ranges
 - Theta, Alpha, Beta, Gamma
- Extracted 3 statistical parameters across each frequency range

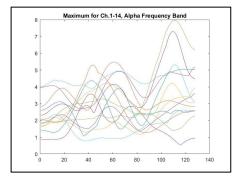
Input:

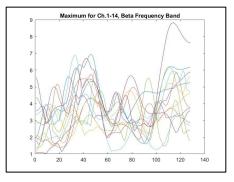
400 x [14x128]

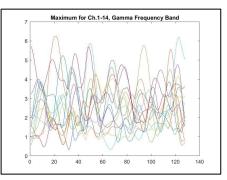
Output:

400 x [3x4x14]









CWT Filter - Approach 2

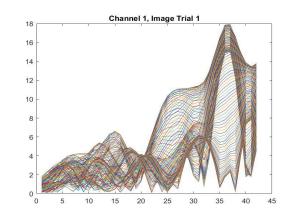
• 42 complex-valued signals were decomposed for each channel

Input:

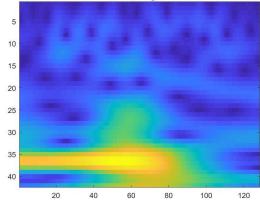
400 x [14x128]

Output:

400 x [42x128x14]

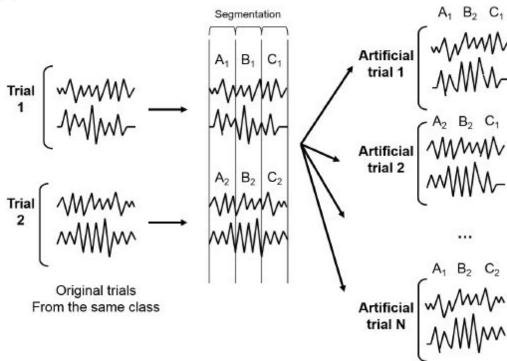


Channel 1, Image Trial 1



Data Augmentation

- Divide each EEG signal first into k segments
- Randomly reconstruct signal



Img Ref: Lotte, F. (2011). Generating Artificial EEG Signals To Reduce BCI Calibration Time. 5th International Brain-Computer Interface Workshop, 5th International Brain-Computer Interface Workshop, 2011.

Modeling - Keras Framework

- I. Raw Signal (Baseline)
- II. Multiple Extracted Features based on the Band-pass filter with Data Augmentation
- III. CWT
 - i. Statistical Parametersii. 2D Imagesiii. 2D Images with Data Augmentation
- # of examples = 400
- # of training examples = 360
- # of testing examples = 40

Raw Signal Modeling (Baseline)

Input: Minimally filtered EEG data (Low-pass filtering with a Nyquist cutoff of 40 Hz)

1) CNN

	conv3×3-6	conv3×3-12	conv3×3-24	FC-128	FC-2
Input	ReLU	ReLU	ReLU	ReLU	Softmax
(42×42)	Max_Pooling	Max_Pooling	Max_Pooling		

2) RNN

model.add(LSTM(128, input_shape=(timesteps, 14)))

model.add(Dense(1,activation='sigmoid'))

model.compile(loss='binary_crossentropy', optimizer='adam',metrics=['accuracy'])

3) Results

The accuracy for both model is around 50%, chance level.

Pre-processing and data augmentation are important to increase accuracy.

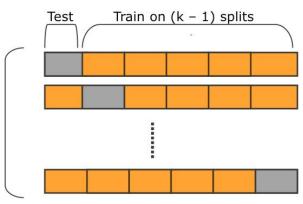
Cross-Validation & Random Seed

1) Ten-fold cross-validation (Training-to-testing ratio = 0.9)

Examples are partitioned into ten equal sized splits. In each process, one split is retained for testing and the remaining nine splits are used for training. The process is repeated 10 times with the 10 results averaged to be the evaluation criteria to make the model more robust.

2) Fixed random seed

Reproducibility is ensured.



k-fold

CNN Model for 5 Extracted Features Input

Filtered Data Size = 56 bands × 14 channels × 5 features

Reshaped Input Size = $28 \times 28 \times 5$

Data augmentation was applied across all 400 examples prior to the preprocessing.

600 artificial trials were generated for each label.

The model is trained with 1440 examples and tested on the rest 160 examples by 10-fold CV.

	conv3×3×3-6	conv2×2×2-12	conv3×3×3-24	FC-56	FC-1
Input	ReLU	ReLU	ReLU	ReLU	Sigmoid
(28×28×5×1)		Max_Pooling 2×2×2	Max_Pooling 2×2×2		

The model with best accuracy is outlined below with Adam optimizer:

Results & Comments

3D CNN with Early Stopping	Mean (std) = 74.38% (3.61%)
Patience = 10	Max = 80.62% Min = 66.88%
3D CNN	Mean (std) = 76.19% (6.64%)
Epoch Number = 55	Max = 85.62% Min = 64.38%

Comments:

Augmenting data over the entire dataset may result in the problem of *information leaking*. Hence the evaluation of this model cannot be considered as accurate. For future models, data will be augmented within training set only.

CNN Model for CWT Statistical Parameters

Filtered Data Size = 3 features × 4 bands × 12 channels

(1st and 14th channels are removed for the possibility to be impacted by eye movement artifacts)

Reshaped Input Size = 6×6×4×1

The model is trained with 360 examples and tested on the rest 40 examples by 10-fold CV.

The model with best accuracy is outlined below with Adam optimizer:

	$conv 2 \times 2 \times 2$ -6	conv 2×2×2-12	conv 2×2×2-24	FC-10	FC-1
Input	Linear	Linear	Linear	Linear	Sigmoid
(6×6×4×1)		Max_Pooling 2×2×2	Max_Pooling 2×2×2		

Results & Comments

Different numbers of epochs and batch sizes were tested with only original data. The optimal result is listed as below:

Batch size =50	Epoch N	Number = 100	
Mean (std) = 62%	(7.81%)	Max = 75%	Min = 47.5%

Comments:

Three features for each CWT filtered signals are not sufficient to develop a good model.

CNN Model for CWT 2D Images

Image Size = 42 decomposed signals × 14 channels × 126 time points (except the first and the last time point)

Reshaped Input Size = 42×42×42

The model with best accuracy is outlined below with Adam optimizer:

Input	conv 3×3×3 -6	$conv3 \times 3 \times 3-12$	$conv3 \times 3 \times 3-24$	conv 3×3×3 -24	conv 3×3×3 -48	FC-10	FC-1
42×42×42×1	Linear	Linear	Linear	Linear	Linear	Linear	Sigmoid
			Max_Pooling 2×2×2		Max_Pooling 2×2×2		

Different numbers of epochs and batch sizes were tested with only original data from subject 1. The optimal result is listed as below:

Batch Size = 180		Epoch Number = 30	
Mean (std) = 71%	(6.04%)	Max = 82.5%	Min = 60%

This best performing pre-processing method and model is applied across all 38 subjects. The max accuracy (average over ten folds) is 79.5% for subject 33 and the min accuracy is 59% for subject 16. The mean accuracy over 38 subjects is 67.74%.

CNN for 2D Images with Data Augmentation

Data augmentation was also applied to this model and evaluated with subject 33.

To prevent from information leaking, the data augmentation was applied on the training set only within each fold to keep the datasets independent. Different numbers of segments (1, 2, 3, 6, 7, 9, 14, 18, 21, 42) and augmenting size (600, 1800) are tried.

600 image trials generated per label

- 3 segments per signal
- Average accuracy across 38 subjects increased by 0.76%
- 24 subjects increased in testing accuracy
- 2 subjects produced the same accuracy
- 12 subjects declined in accuracy
- Subject 20 improved 4.5%

 Table Ten-Fold Cross-Validation Prediction Results for subject 33 with

 Artificial Data

(23 Epochs, Batch Size = 400, Augmenting Size = 600, Max improvement in bold)

#Segment	Mean (std)	#Segment	Mean (std)
1	79.50% (6.30%)	9	78.25% (7.08%)
2	79.50% (7.40%)	14	77.75% (6.75%)
3	81.25% (5.15%)	18	78.25% (7.59%)
6	77.75% (5.86%)	21	79.25% (6.03%)
7	78.25% (6.43%)	42	77.75% (5.96%)

Table Ten-Fold Cross-Validation Prediction Results over 38 subjects with Artificial Data

(10 Epochs, Batch Size = 400, Segment number =3, Augmenting Size= 1800, Subjects with improvement in bold)

Subject	Mean (std)	Subject	Mean (std)
1	67.25% (2.84%)	20	71.75% (6.71%)
2	73.75%(4.64%)	21	66.75% (5.48%)
3	63.25%(5.60%)	22	69.25% (6.62%)
4	75.50% (5.34%)	23	68.50% (8.67%)
5	78.50% (6.91%)	24	62.25% (7.54%)
6	73.25% (6.62%)	25	70.50% (6.60%)
7	61.50% (8.23%)	26	74.25% (5.25%)
8	68.75% (9.10%)	27	77.00% (4.30%)
9	71.00% (5.15%)	28	69.50% (7.73%)
10	67.00% (6.10%)	29	68.25% (7.16%)

11	68.50% (4.50%)	30	77.50% (5.00%)
12	65.25% (5.96%)	31	61.00% (5.27%)
13	73.75% (3.91%)	32	66.00% (4.21%)
14	72.75% (6.27%)	33	80.00% (5.70%)
15	63.75% (4.91%)	34	65.75% (7.08%)
16	61.50% (9.03%)	35	67.75% (6.93%)
17	66.75% (3.17%)	36	62.75% (5.64%)
18	67.75% (5.18%)	37	62.00% (6.96%)
19	67.50% (8.29%)	38	68.25% (6.90%)
Mean: 68.	Mean: 68.85%		ax: 61% - 80%

1800 generated images

- Average accuracy across 38 subjects increased by 1.11%
- Subject 4: improvement of 5.25%
- 29 subjects increased testing accuracy
- 1 subject produced the same result
- 8 subjects decreased testing accuracy

Future Work

- 1) CWT pre-processing technique
 - 3D Matrix

Input

- 2) Data Augmentation
 - Increase the amount of generated data

Thank you!

Q & A