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Applied Computational Intelligence Laboratory

Convolution and Wavelet Neural Networks Applied to EEG Brain-Control Interface

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Opportunities for Undergraduate Research Experiences

Introduction

Electroencephalography (EEG) for a brain-control interface (BCI) is the recording of electrical activity on the scalp for the purpose of providing a direct communication pathway to an external device. This technology has the potential to be a primary method of interaction for individuals with certain injuries or abnormalities.

Figure 1: EEG Headset

[Photo by Chris Hope, http://creativecommons.org/licenses/by/4.0/]

Research Objectives

- Provide an overview of the most effective technology in EEG BCI research
- Determine the possibility of using deep learning convolution and wavelet neural networks for EEG BCI
  - Create an effective Convolution Neural Network (CNN) to classify BCI motor imagery effectively
  - Use heuristic from CNN learned model to generate a Wavelet NN

EEG BCI System Overview

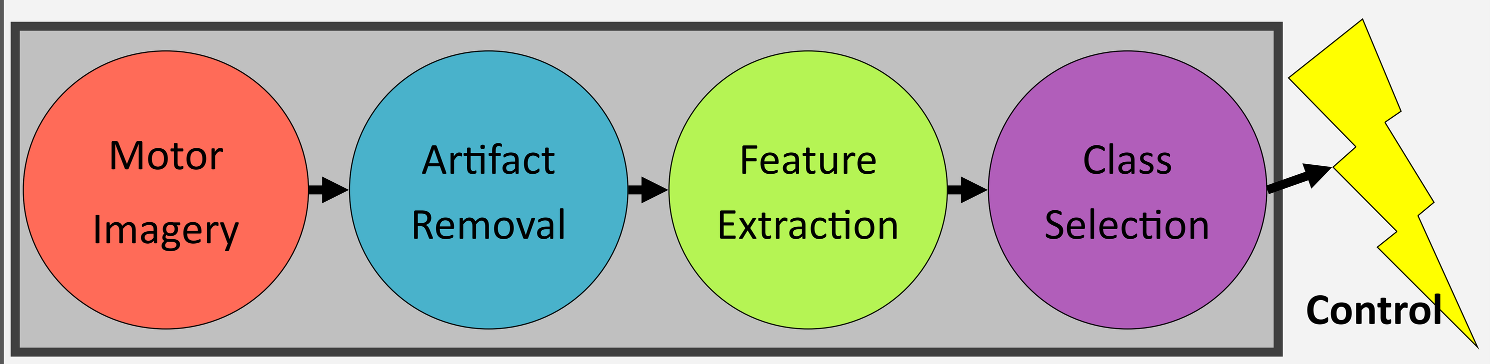

Figure 2: EEG BCI System Overview Diagram (original)

Data Set

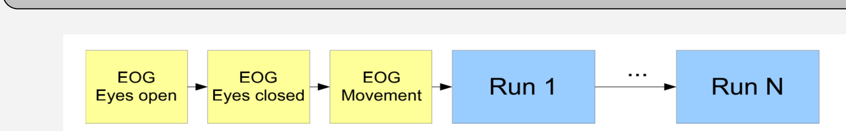

Figure 3: BCIC IV 2b Session Analysis [1]

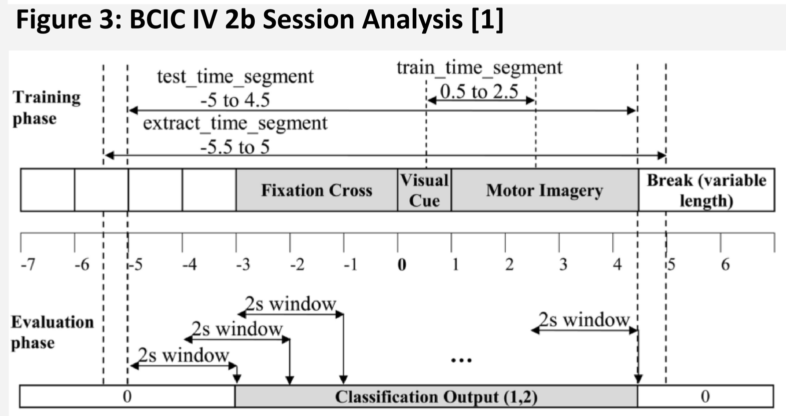

Figure 3: BCIC IV 2b Trial Analysis Extraction Segment [2]

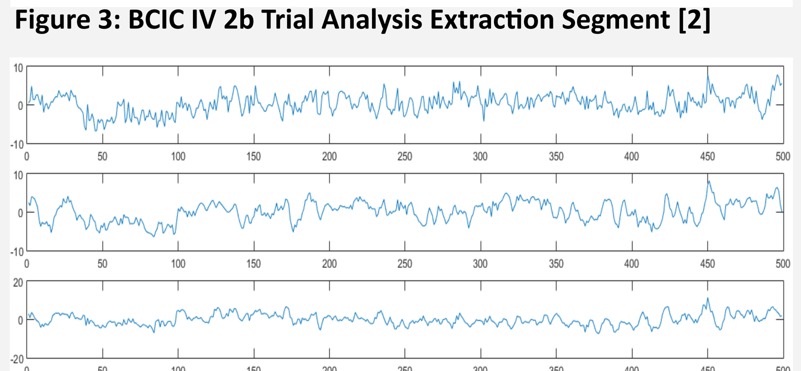

Figure 4: BCIC IV 2b Trial Segment, Matlab (original)

- Used BCI Competition IV 2a and 2b Datasets
- Takes advantage of Motor Imagery for control mental process
- Mental Imagery activates specific areas on the motor cortex that can be used to distinguish control intent
- Why use existing data?
  - Comparable results from other researchers
  - No human testing permissions needed

Methodology

Artifact Removal, Pre-processing

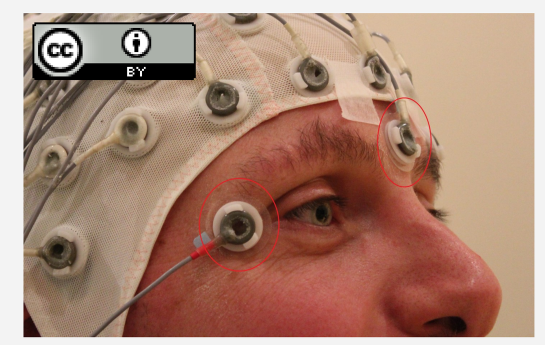

Figure 5: EOG Channel View

[Photo by Chris Hope, https://creativecommons.org/licenses/by/2.0/]

- **Artifact Removal**
  - Best way for artifact removal uses Electrooculogram (EOG)
  - EOG channels show electric field from eye that causes artifacts in EEG data
  - Artifact removal algorithm given in [3]
- **Pre-processing**
  - Can potentially use Principal Component Analysis (PCA) [4]
  - This was ineffective in practice

Feature Extraction

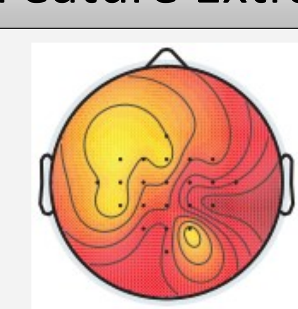

Figure 6: Spatial Activation View [5]

- **Techniques Explored**
  - Common Spatial Patterns (CSP) [2]
  - Feature Bank CSP (FBCSP) [2]
  - Independent Component Analysis (ICA) [5]
  - Analytic Wavelet Transform (AWT) [6]
  - Fourier Transform (FT) [7]

Classifier

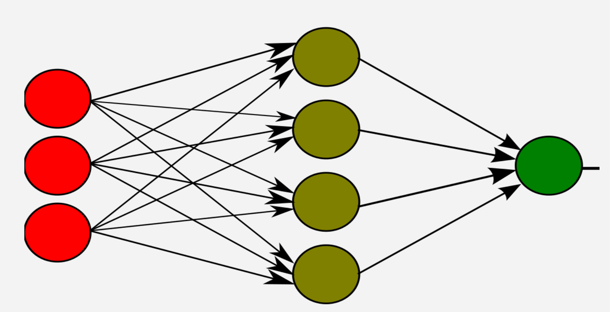

Figure 7: Multi-Layer Perceptron Diagram

By Sky99 (own work) [CC BY-SA 3.0 (http://creativecommons.org/licenses/by-sa/3.0)], via Wikimedia Commons

- **Multi-Layer Perceptron (MLP) [8]**
  - Network design is important
  - Nonlinear decision boundary
  - This was used for experimentation
- **Support Vector Machine (SVM)**
  - Linear decision boundary
  - Very fast to learn

Feature Extraction + Classifier

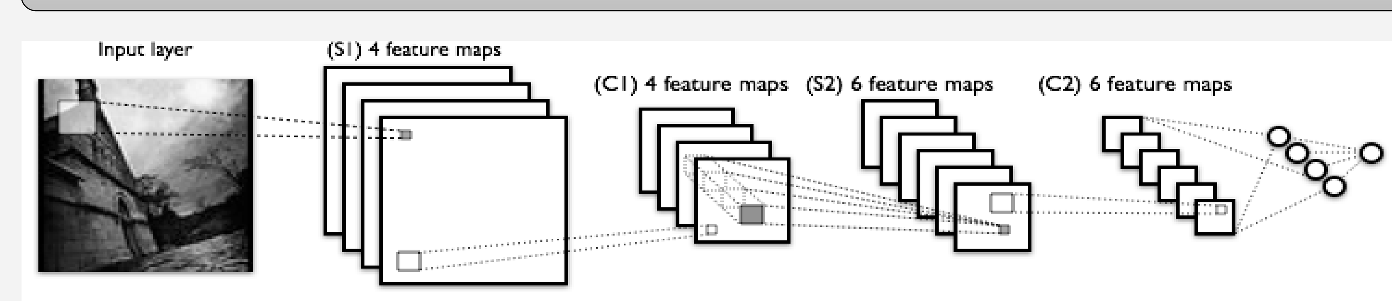

Figure 8: Convolution Neural Network, credit: http://deeplearning.net/tutorial/lenet.html

- **Convolution Neural Network [7]**
  - adaptive feature extraction
  - Network design is important
- **Wavelet Neural Network [9]**
  - Static Feature extraction
  - Fewer hyper-parameters

Test Setup

All tests were performed where the classifier was given only training data from the specific subject for which test data was evaluated. This gives the best success indicator without skew from training data selection.

Experimental Results

Experiment 1: Feature Bank CSP

- Feature extraction technique given in [2]
- Classifier composed of MLP hidden layer size of 50
- Baseline for comparison
- Sometimes under-fitting training data

Subject	Train K	Class K
B01	0.38	0.08
B02	0.27	0.04
B03	0.32	0.12
B04	0.90	0.46
B05	0.72	0.34
B06	0.54	0.36
B07	0.50	0.24
B08	0.37	0.41
B09	0.49	0.23
Averages	**0.50**	**0.25**

Table 1: FBCSP Classifier Results

Experiment 2: Wavelet Feature Extractor

Subject	Train K	Class K
B01	0.40	0.03
B02	0.23	0.05
B03	0.19	-0.05
B04	0.70	0.28
B05	0.29	-0.02
B06	0.20	-0.03
B07	0.43	0.19
B08	0.34	0.34
B09	0.37	0.06
Averages	**0.35**	**0.095**

Table 2: Wavelet Classifier Results

- Features from covariance matrix of analytic Morlet wavelet transform across the three signals
- Classifier composed of MLP with a hidden perceptron layer of 50
- Results show over-fitting, and insignificant test rate

Experiment 3: Convolution Neural Network

- Composed of 16 3x3 kernels, 32 2x2 kernels, and 256 perceptron layer connected to 2 classes
- Implemented using Nvidia CUDA and ConvNet
- Low scores on testing data
- Over-fitting on almost all trials
- Test results show insignificant classification rates

Table 3: CNN Classifier Results

Subject	Train K	Class K
B01	0.55	0.07
B02	0.69	-0.07
B03	0.77	0.04
B04	0.79	0.16
B05	0.71	0.16
B06	0.86	0.08
B07	0.68	0.05
B08	0.76	0.24
B09	0.61	0.06
Averages	**0.71**	**0.094**

Conclusions

Kappa	Percent
0.7	85%
0.5	75%
0.25	62%
0.1	55%

- FBCSP doesn't perform very well when only given data from a single patient to train on
- The CNN is over fitting and ineffective for a patient-specific classifier, but may be more effective given selected data from other patients
- The wavelet-based feature extractor does not perform well, but may improve with testing of additional wavelet functions

Future Work

- Use High Performance Computer with genetic algorithm to select training examples and generate acceptance criteria for training CNN across all patients
- Implement simple classifier on portable device that could be used in practical environments

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