Analyzing EEG Brainwaves to Decode Attentional State for Faces and Scenes

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Contents

Introduction

Problem Description

- Attention is essential in human cognition.
- Deficits in attention are common in brain disorders:
    - *Alzheimer's, Traumatic Brain Injuries, PTSD*
- EEG has become an important tool for assessing and training attention.

Proposed Solution

- Develop a convenient, generalizable neurofeedback-based technology for attention training.
    - *Brain attention training tech using EEG and BCI.*
- Conducting attentional training to collect EEG data.
- Create a neural network model to decode attentional states from brainwaves.

Development of the BCI Platform

- **EEG Recording Device**
  - The BCI platform includes *UNICORN HYBRID BLACK*, a workstation, and Python-based software with a GUI.

- **Interface**
  - A wireless headset captures EEG signals, and a custom GUI manages visual stimulation and protocol adjustments.

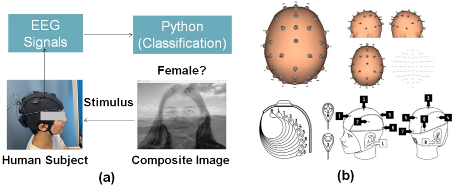

Figure: The BCI platform a) A schematic of the EEG-based BCI system. b) The electrode positions of the cap: Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8, according to the 10/20 system.

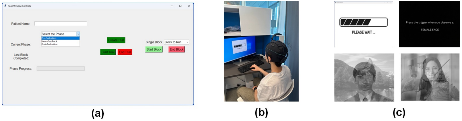

Figure: Dual-monitor workstation a) Experimenter workstation. b) Subject c) Subject' s workstation.

Experimental Protocol

- **Procedure:** Participants were trained to focus their attention on specific image categories and respond via a trigger button during eight blocks of trials, each block containing 40 image stimuli.
- **Stimuli:** The stimuli were composite images, with equal transparency from two categories. The task-relevant images made up 90% of the images in each block.
- **Duration:** The experiment took about 15 minutes per participant, with each block running once to prevent fatigue.

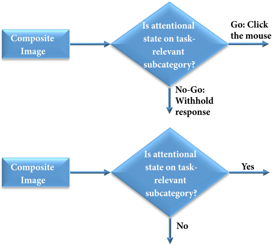

Figure: Experimental Protocol.

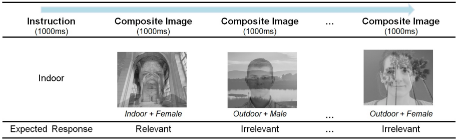

Figure: A sample sequence of trials.

Signal pre-processing

- **Filtering:** A band-pass filter (0.1 to 30 Hz) was used to preserve relevant EEG frequencies.
- **Denoising:** K-nearest neighbors regression algorithm was applied to remove potential noise from the data.

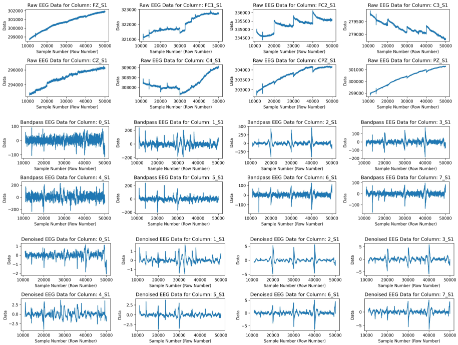

Figure: Sequential preprocessing steps: from raw data to band-dassed and denoised data.

Data Preparation and Processing Pipeline

- **Windowing:** Continuous data was divided into 1-second windows, each encapsulating 250 data points.
- **Reshaping:** Each 40-millisecond segment is considered as one sample, creating an array of 288 samples. (*288 samples, each composed of 25 segments, with 10 data points and 8 channels*)
- **Oversampling:** The minority class instances were duplicated to balance the dataset.
- **Splitting:** The dataset was split into training (90%) and testing (10%) sets. An untouched set was also reserved for validation.
- **Reshaping for CNN:** The training and testing datasets were reshaped into 4-dimensional arrays to prepare for CNN processing.

Classification Method

Multilayer Perceptron (MLP)

- Comprises an input, two hidden, and an output layers.
- Employs 'relu' activation function and dropout regularization.
- Uses 'rmsprop' optimizer and categorical cross-entropy loss function.
- Trained for 20 epochs with a batch size of 32.

Convolutional Neural Network (CNN)

- Comprises a single convolutional layer and three dense hidden layers.
- Employs ReLU activation function and softmax for output.
- Uses 'Adam' optimizer and categorical cross-entropy loss.
- Evaluated over 20 epochs with a batch size of 32.

Support Vector Machine (SVM)

- Uses Radial basis function (rbf) kernel and one-vs-rest (ovr) decision function shape.
- 'gamma' parameter is set to 'auto'.
- Performance is evaluated based on accuracy.
- Employs Hilbert transform for feature extraction.

Results

- MLP achieves higher accuracy than CNN for subjects 1-4, with MLP at 92% and CNN at 91%.
- The SVM model struggles to predict any of the four classes with more than 30% precision rate. .

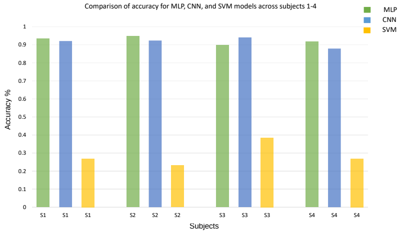

Figure: Comparison of accuracy for MLP, CNN, and SVM models across subjects 1-4.

- As epochs increase, both models exhibit decreasing loss function and improving accuracy.
- CNN model exhibits more smoothness.

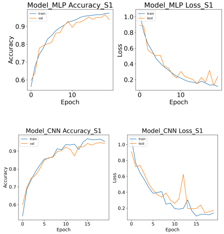

Figure: Comparison of accuracy and loss metrics for MLP and CNN models over subjects 1

Results

Table: Comparative evaluation of precision across different models for each class across all subjects

Subject Number	Precision %			
	Female	**Male**	**Indoor**	**Outdoor**
S1	MLP: 0.94 CNN: 0.90 SVM: 0.75	MLP: 0.94 CNN: 0.90 SVM: 0.18	MLP: 0.87 CNN: 0.97 SVM: 0.00	MLP: 0.99 CNN: 0.90 SVM: 0.50
S2	MLP: 0.94 CNN: 0.89 SVM: 0.00	MLP: 0.95 CNN: 0.95 SVM: 1.00	MLP: 0.95 CNN: 0.94 SVM: 0.00	MLP: 0.89 CNN: 0.89 SVM: 0.20
S3	MLP: 0.81 CNN: 0.94 SVM: 0.00	MLP: 0.96 CNN: 0.97 SVM: 0.30	MLP: 0.93 CNN: 0.91 SVM: 0.14	MLP: 0.89 CNN: 0.94 SVM: 0.40
S4	MLP: 0.83 CNN: 0.86 SVM: 0.50	MLP: 0.94 CNN: 0.37 SVM: 0.16	MLP: 0.91 CNN: 0.87 SVM: 0.20	MLP: 0.96 CNN: 0.90 SVM: 0.50

Discussion

Performance Analysis of Models

- MLP model hits 92% accuracy, CNN trails slightly at 91%.
- The CNN model exhibits smoother accuracy and loss function plots.
- The CNN model operates slower than the MLP model.
- The SVM model struggles with the effective prediction of the four class categories, not exceeding a 30% precision rate.
- Our MLP and CNN model surpasses the 77% accuracy benchmark set by a previous study [1].

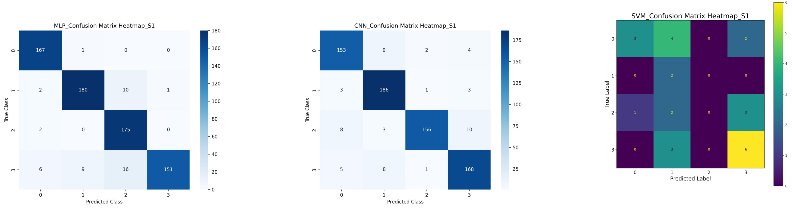

Figure: Comparison of confusion matrix Heatmap for MLP, CNN and SVM models over subjects 1

Conclusion

- A new EEG-based BCI classification system was developed for evaluating attention during a visual discrimination task.
- Four participants were recruited to test the system's feasibility and evaluate the viability of EEG-based classification of attentional state.
- EEG signals are collected from the whole brain and sent to the computer for processing.
- Data is classified into four distinct categories: Female, Male, Indoor, and Outdoor.
- Three types of models were developed and implemented: MLP, CNN, and SVM.
- The average classification results between the four categories were approximately 91.75%, 91.25%, and 23.75%, for MLP, CNN, and SVM, respectively.
- In conclusion, our deep neural network approach effectively streamlines EEG signal classification, offering significant potential for advancements in non-invasive brain signal analysis.

Refrences

[1] Reza Abiri, Soheil Borhani, Yang Jiang, and Xiaopeng Zhao. Decoding attentional state to faces and scenes using eeg brainwaves. *Complexity*, 2019, 2019.

Thank you :)