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Training a Convolutional Neural Network to Classify Motor Imagery EEG Signals for Brain-Computer Interface Applications

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Abstract

The purpose of this paper is to train a convolutional neural network (CNN) to perform real-time classification of electroencephalography (EEG) signals generated during motor imagery (MI), which is a cognitive process in which subjects imagine themselves performing a movement without even tensing their muscles. Provided that the CNN classifier is consistent, it can be used to generate commands to control a wide variety of systems such as wheelchairs, prosthetics, robots, and computer programs. Traditional methods that do not make use of artificial neural networks (ANN) rely on expensive high-tech lab equipment to counteract the nonlinear, nonstationary, and noisy nature of EEG signals. In contrast, ANNs are more robust to noisy inputs because they depend on the amount of data and training provided to them in order to find informative relationships hidden in signals like EEG. We propose to assess the robustness of this approach by using cheaper equipment and lower electrode counts to generate a classification model and testing its ability to control the position of a robot manipulator in two dimensions. To conduct our experiment, we collected EEG data from one subject using eight electrodes while the subject performed MI tasks that involved imagining the movement of different body parts (4 tasks in total). The data was then transformed into a time-frequency representation and saved as a spectrogram image for each electrode and each trial for each MI condition. Finally, these images were separated into training and testing sets. The first set was used to train the CNN to classify the images into 5 categories (up, down, left, right, and idle), while the second set was used to determine the accuracy of the trained classifier. Finally, although the best classification accuracy of this model peaked at 40%, which, although significantly better than random guessing, was still too low to reliably generate control commands. To overcome this challenge, we attempted to use a leaky-integrate-and-fire (LIF) neuron model to build up commands over time. However, the bias in the network resulted in all commands being classified as a dominant category, which in turn resulted in the robot arm moving in a single direction.

1. Introduction

There has been a recent increase in popularity around Brain-Computer Interfaces (BCIs) mainly due to new technological advances that have made it more affordable to explore the use of these devices for medical[1] and entertainment[2] purposes. BCIs can be classified as invasive and non-invasive, with the main difference being a tradeoff between the signal-to-noise ratio of brain activity that can be recorded and the risk associated with surgical procedures required to implant devices to get more direct measurements[3].

Scientists have discovered several ways to get information from the brain through different brain imaging techniques, one of which is electroencephalography (EEG). EEG is a noninvasive measure of collective brain activity that records the changes in voltage resulting from underlying neural activity patterns. It is often used in BCI approaches because of its high temporal resolution[4], which translates to low latency when sending commands to external devices. However, EEG signals are characterized as being noisy, nonstationary, and nonlinear[8], which makes them quite challenging to analyze and process. Often, we rely on technically advanced mathematical models and specialized hardware to make use of these signals; however, such research-grade lab EEG setups are often expensive and cumbersome to implement outside academic settings.

Modern approaches use deep learning to find models that can address the noisy and nonlinear nature of EEG signals. Inspired by the promising results of these studies[5,6], and the advances in development tools for ANNs, we seek to determine if we can leverage the ability of ANNs to find underlying relationships in data to make low-cost BCI systems more effective. Based on the success of previous papers in classifying datasets like the BCI IV competition dataset[7], we seek to replicate their approach with the low-cost OpenBCI headset based on the premise that signal quality can be compensated by adding more training data. To do this, we have set up a data collection experiment to replicate the motor-imagery (MI) tasks of the original dataset. We then used that data to produce spectrograms and train a convolutional neural network to classify the EEG signals recorded during the different MI conditions into 5 distinct categories that can be interpreted as commands to control a 4 DOF robot manipulator.

2. Methods

2.1. Overview

At the highest level of abstraction, a BCI system can be described as shown in Figure 1. This paper focuses mainly on whether or not the appropriate choice of signal processing submodules can compensate for low signal-to-noise ratios inherent in low-cost signal acquisition devices. Additionally, it is worth noting that due to the modular nature of this description, the application module can have a wide variety of implementations ranging from providing input to software applications to controlling wheelchairs and even robot arms.

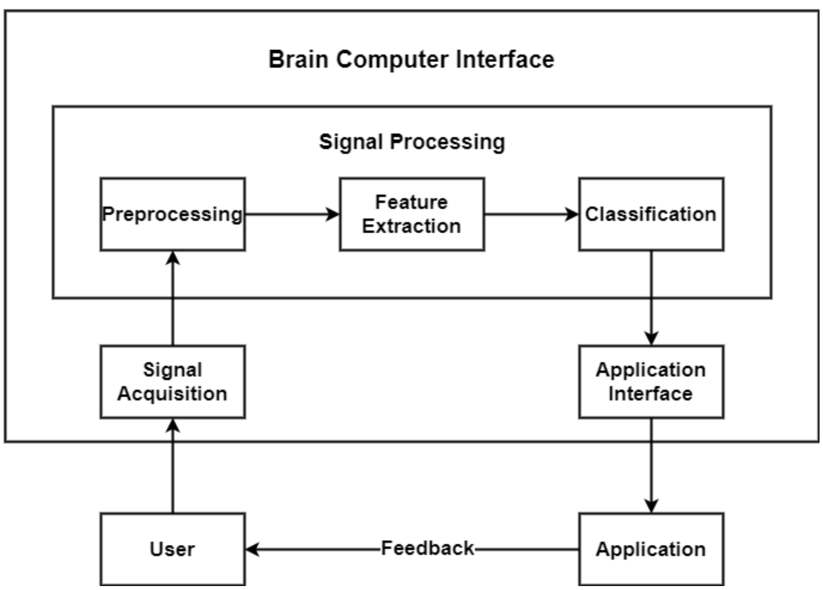

Figure 1. Top-level block diagram of a typical brain-computer interface system.

A more detailed description of our project setup is described following the new terminology proposed by IEEE P2731 in Figure 2. The remainder of this section describes the implementation details of these modules.

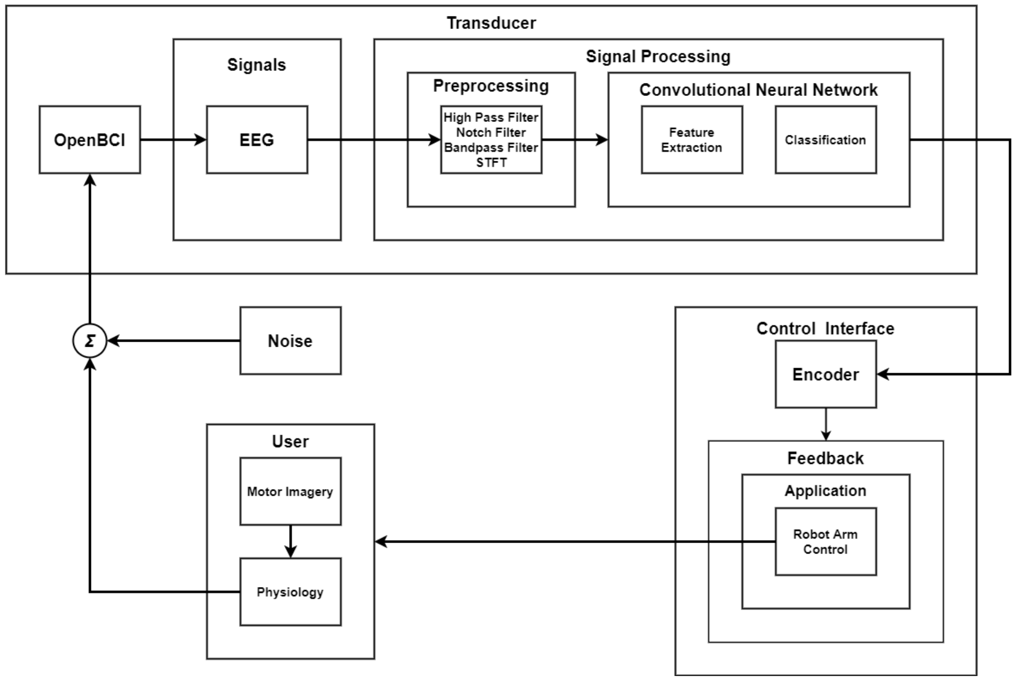

Figure 2. A complete description of the project setup described per the IEEE P2731 standard.

2.2. Experimental Paradigm

The user was equipped with the data acquisition device (see Figure 4) and was asked to imagine movement in response to visual cues presented on the screen. For each trial, the subject was presented with a black screen for 2 seconds. Then a fixation cross was placed in the middle of the screen to inform the subject that a visual cue was approaching and to help minimize noise signals produced by eye movement. Finally, the subject was presented with one of four randomized visual cues: 1) An arrow pointing up which prompted the subject to imagine opening their mouth; 2) an arrow pointing down which prompted the subject to imagine lifting their heels; 3) an arrow pointing left which prompted the subject to imagine clenching their left fist, and 4) an arrow pointing right which prompted the subject to imagine clenching their right fist. Figure 3 shows the structure of a single trial. Data were recorded from the subject in 14 sessions each consisting of 48 trials each.

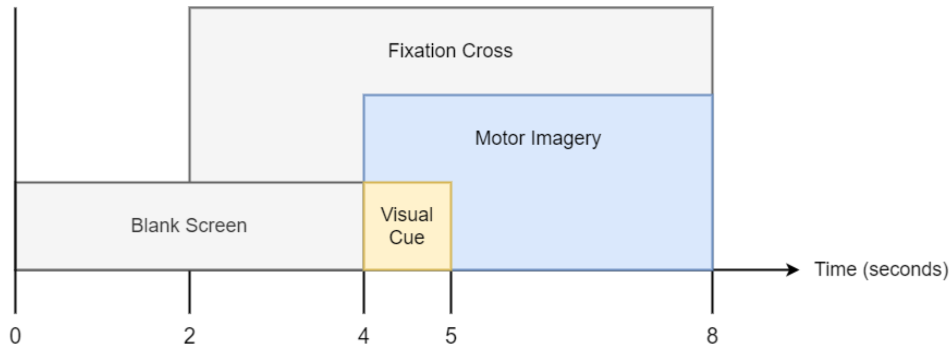

Figure 3. Trial structure during data acquisition.

2.3. Signal Acquisition

The OpenBCI Mark IV is a portable dry-electrode headset that was chosen for this project due to its low cost, easy setup, ample community support, and the variety of software libraries available to interface with it. This headset can record up to 8 EEG channels which can be placed in any of the nodes pictured in Figure 4. Electrode positions Fp1, Fp2, C3, C4, Fz, Cz, CP1, and Cp2 were chosen based on their relative position to the motor cortex, where we expected to see more relevant brain activity as the subject performed the MI tasks defined in the previous section. Data were recorded at 250 Hz, while making sure that the impedances in each electrode remained below 2000 kΩ as recommended by the vendor.

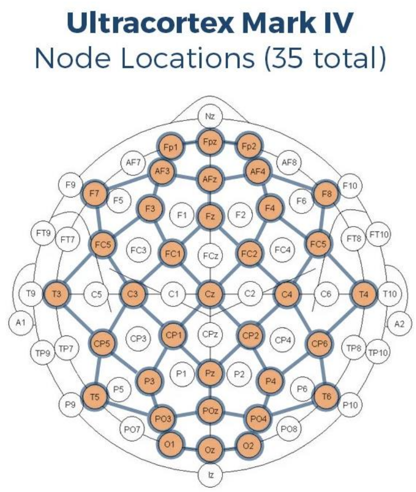

Figure 4. Shown in orange are the available electrode positions compliant with the internationally accepted EEG 10-20 system for electrode placement.

2.4. Signal Processing

2.4.1 preprocessing

The raw EEG data recorded during the different sessions was stored as a .csv file and then uploaded to a different program to start a preprocessing pipeline. First, a high-pass filter of 0.5 Hz was applied to all channels in order to remove any DC offsets in the signals. Then, a notch filter was applied at 60 Hz to remove power line noise coming from the environment. Next, a band-pass filter was applied with a center frequency of 19 Hz and a bandwidth of 12 Hz to limit signal analysis to the 7-31 Hz frequency range which is known to encode conscious cognitive activity such as imagining motor movement. Finally, a short-time Fourier transform (STFT) was applied to each individual channel to generate a spectrogram representing the time-frequency information as an image with 8 channels as illustrated in Figure 5. The STFT was applied to 3-second segments starting 0.5 seconds after the visual cue onset. The number of samples per segment for the STFT was 128, and the number of overlapping samples was 127. The generated images were then stored as .tif files to be used by the convolutional neural network (CNN).

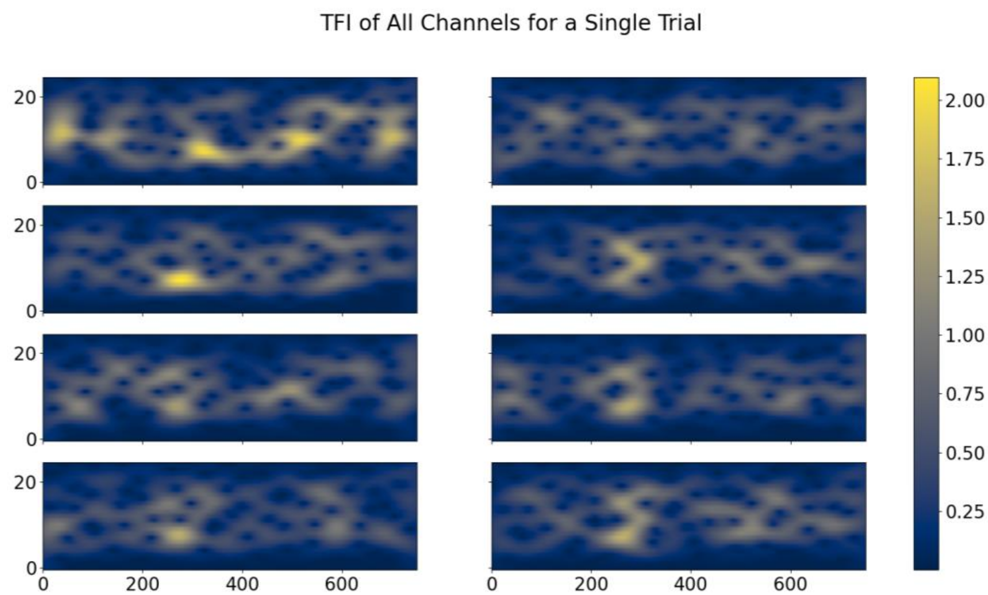

Figure 5. Time-Frequency Image (TFI) of a single trial. Each subplot represents one electrode channel. The y axis represents the range of frequencies analyzed, and the x-axis represents the number of samples in a trial.

2.4.2. feature extraction and classification

CNNs have the characteristic that they can perform feature extraction and classification in one step. Our choice for the architecture was based on a previous study[7] that explored the efficiency of neural networks when performing data augmentation for MI EEG classification tasks. A detailed description of the architecture is shown in Table 1 while an illustration is provided in Figure 6.

Table 1. Convolutional neural network architecture described sequentially from top to bottom.

Layers	Filter Size	Output Dimension	Activation	Notes
Input		(64, 64, 8)		
Convolution	(3, 3)	(62, 62, 128)		
Max-pooling	(2, 2)	(31, 31, 128)	ELU	
Dropout		(31, 31, 128)		rate = 0.5
Convolution	(3, 3)	(29, 29, 128)		
Max-pooling	(2, 2)	(14, 14, 128)	ELU	
Dropout		(14, 14, 128)		rate = 0.5
Batch Normalization		(14, 14, 128)		momentum = 0.6
Convolution	(3, 3)	(12, 12, 64)		
Max-pooling	(2, 2)	(6, 6, 64)	ELU	
Dropout		(6, 6, 64)		rate = 0.5
Batch Normalization		(6, 6, 64)		momentum = 0.6
Convolution	(3, 3)	(4, 4, 32)		
Max-pooling	(2, 2)	(2, 2, 32)	ELU	
Dropout		(2, 2, 32)		rate = 0.25
Flatten		(128)		
Dense		(100)	ELU	
Dropout		(100)		rate = 0.25
Output		(5)		

The spectrogram images generated during the 14 sessions were split into a training and a testing set using a 9:1 ratio. Then the neural network was trained over 350 epochs using a batch size of 5 images per epoch, using “Adam” as the optimizer with a learning rate of $1x10^{-4}$ and a categorical cross-entropy loss function.

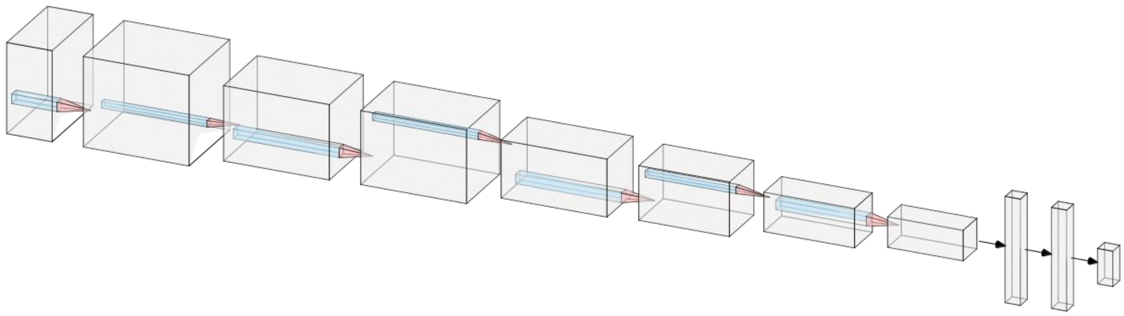

Figure 6. Visual description of the CNN architecture used in this project.

3. Results

The accuracy results during training can be observed in figure 6. From the data in the figure, we can infer that the classifier is overfitting the training images, and although, on average, the validation accuracy rate is better than random guessing (0.2), the results in figure 7 show that a majority of the TFIs tend to be misclassified at significant rates. In an ideal scenario, figure 7, should look like a diagonal matrix with all the values, not on the diagonal close to zero.

We tried feeding the output of the CNN to a leaky integrate-and-fire model to control a robot manipulator, but the classifier was biased towards classifying almost all real-time images as “move_right”, making the robot arm move right at a constant rate regardless of the user’s intention. A link to the video of this demonstration can be found in the reference section[9].

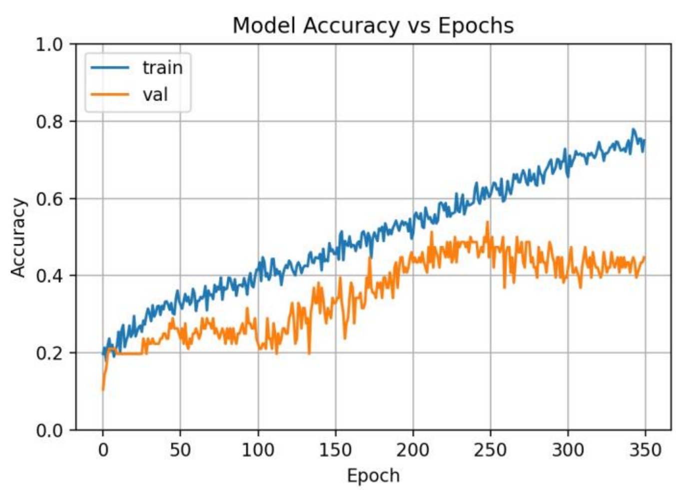

Figure 6. Model accuracy trend as a result of the number of epochs used during training.

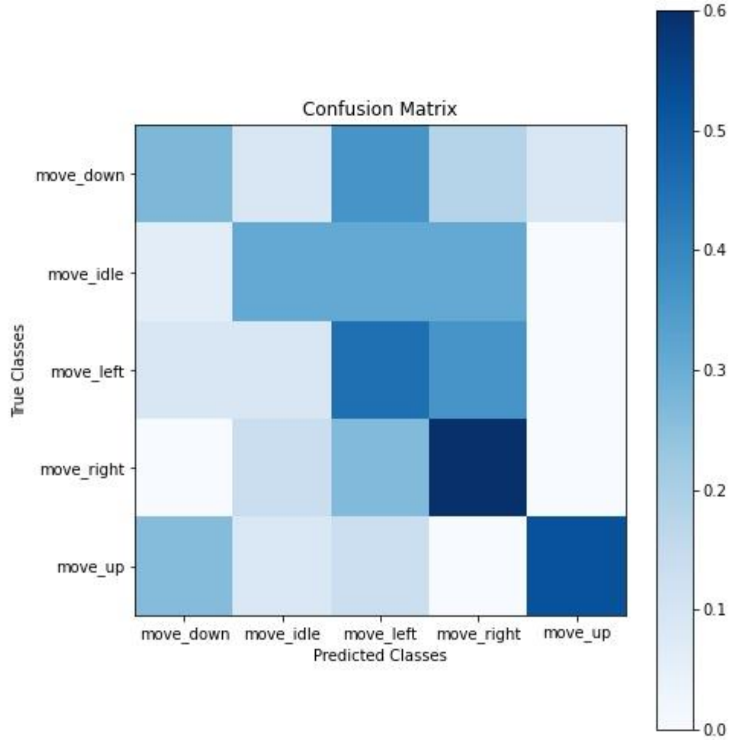

Figure 7. The confusion matrix of the classification model normalized along each true class.

5. Conclusion

It has been demonstrated in other studies that CNNs and hybrid ANN models, in general, achieve classification rates of up to 90%[5] for MI-EEG tasks. It is apparent that the CNN in this study was able to find a relationship between the MI-EEG data and the command labels, but this relation is not strong enough to be used reliably in a BCI. The causes for such low accuracy are unclear. It is possible that simply recording more data would result in a better model, or it could be due that the inherently lower signal-to-noise ratio of the dry-comb electrodes is just not suitable for this type of application.

Additionally, it is worth noting that one of the main differences between our dataset and the one used in the original papers are factors like electrode count (8 vs 64), number of subjects (1 vs 9), and the use of dry vs. wet electrodes. Another source of error in real-time classification might come from connecting the robot to the same machine that is recording EEG. EEG signals tend to be sensitive to power line noise, and the robot manipulator might be amplifying the noise in the recordings.

Future work should start by assessing the signal-to-noise ratio of the data acquisition device, and then online classification should be attempted without connecting the robot manipulator to the same machine. Additionally, approaches like data augmentation and normalization should be explored to improve the quality of the dataset.

6. References

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