EEG Brain-Computer Interface

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***Abstract*—Brain-computer interfaces are devices that enable direct communication between the brain and a computer, allowing users to control various applications with their brain activity. An electroencephalogram, a device that can measure brain activity through electrodes attached to the scalp, can be used to build a non-invasive (not requiring surgery) brain-computer interface. This technology has a large potential impact for accessibility devices for those with motor impairments and for immersive gaming experience. The goal of this project was to build a non-invasive brain-computer interface binary game controller. To achieve this, we built and tested multiple models, including a statistical classifier, a convolutional neural network, and a singular vector machine. The statistical classifier achieved 81.36% accuracy, the neural network had 92.84% but struggled to generalize, and the singular vector machine achieved 94.43%. Finally, the models were integrated as the control mechanism for a custom version of the game Flappy Bird.**

I. Introduction

A. Motivation

Brain-computer interfaces (BCIs) are devices that facilitate direct communication between the brain and a computer, enabling the control of computer inputs (mouse or keyboard inputs), robots, or prosthetics. Neurotechnology and BCIs have gained increasing attention in recent years, jointly due to the popular public demos of Neuralink [1] and the ever decreasing cost of entry for non-invasive research. While invasive BCIs promise much higher acuity and wider applications, non-invasive BCIs such as those based on the electroencephalogram (EEG) can provide a reliable and affordable way to measure brain activity build BCI systems. EEG BCIs are especially attractive for building consumer technology, as they are much cheaper, safer, and there is no procedure needed to use one.

The consumer market for BCIs is currently relatively untapped, especially when one considers the potential for consumer applications namely with virtual reality (VR). There were approximately 50 million VR devices sold globally between 2014-2021 with 16.44 million of those sales in America alone [2] [3]. The market was valued at $21.83B in 2021, and is expected to grow by 15% from 2022-2030 [4]. VR promises a more immersive media/gaming experience, but the immersion is limited by the controls. EEG BCIs offer a unique solution to this problem, as the electrodes can be built directly into a headset and the ability to control the device with your thoughts is about as immersive as you can get.

The other major application of non-invasive BCIs is for people who have impairments in their motor function due to various conditions. Many of such people may not want or be able to undergo a surgical implantation of a BCI device, which limits their options for interacting with computers and the world around them. Non-invasive BCIs offer a more convenient and comfortable alternative that can enable them to communicate and control devices using only their brain activity.

B. Related Works

The notion of building EEG BCIs has been around for a while. Though consumer devices are currently uncommon, there are a handful of companies working on these devices. One such company, Interaxon Inc., recently launched a software development kit and EEG headband explicitly designed for use in VR systems [5]. Outside of VR and consumer devices, much work has been done in research settings for BCI game controller. Liao et al. [6] presented a BCI game controller using novel sensors in 2012. Advancements have also been made in improving the classification models powering BCIs. One of the most prevalent of such models is EEGNet [7], a convolutional neural network (CNN) architecture that manages competitive performance with significantly fewer parameters than comparable models. Another interesting model is EEG-Conformer [8], a convolutional transformer network that combines spatial-temporal convolutions, pooling, and self-attention to effectively classify EEG data.

C. Problem Definition

The combined human aid and consumer market potential for non-invasive BCIs is massive, yet these kinds of devices are still rare in the real world. We set out to build a robust simple game controller using a relatively cheap EEG, OpenBCI's Ultracortex Mark IV with the 8-channel Cyton board. Using this device, we aimed to build a binary controller and applied it to play a custom version of the game Flappy Bird.

Most effective research and production EEG BCI systems use much more expensive hardware, including more electrodes and electrodes of higher quality reducing the noise in the brain signals. Due to budget constraints we were limited to cheaper hardware with lower fidelity signal. This issue leads to three guiding principles in building a BCI system: extensive signal processing to compensate for the noisy signal, using signals that are maximally reflected in the data as control inputs, and a careful training process to avoid overfitting noise patterns in the signal.

II. Methodology

A. Target Control Signal

At the onset of the project we explored multiple potential control signals. The first attempt was to use thought signals (i.e. thinking ”jump”), however we quickly found there simply wasn’t enough relevant signal in the EEG readings. Similarly, we experimented with motor imagery signals such as thinking about arm movements or jumping, but again these patterns were indiscernible in the data. Finally, we settled on physical motor movements. We considered using arm or leg movements, but in the joint interest of keeping the system maximally useful for those with disabilities and having as strong of a signal as possible, we decided to use blinking as the control mechanism.

B. Data Collection

For both data collection and control integration, we built a custom version of Flappy Bird written using PyGame. The EEG data stream was integrated into the game using Brainflow, and we built two game modes for interfacing with the device: data collection and BCI control. In both modes the headset is connected to and data is constantly streamed into a buffer from the device on launch. In data collection mode, the user plays the game using the spacebar to jump, and is instructed to blink anytime they press space. The program then listens for the spacebar press, and inserts a marker in the EEG data. On exit the data is formatted and written to a csv file. In BCI mode, the program evaluates each packet of 255 data points, feeding the data into the model to determine whether or not to jump.

Data is streamed at 250hz in packets of 255 readings, including voltage readings from each of the eight EEG electrodes, accelerometer data, timestamps, and some other unused readings. We only used EEG readings for our models. Importantly, readings from the EEG are scaled by a factor given by:

$$\frac{4.5V}{\text{gain}} \times \frac{1}{(2^{23}-1)},$$

where gain is a user-configurable value of: 1x, 2x, 4x, 6x, 8x, 12x, or 24x. For our work we used the maximum gain (24x), and therefore had to scale data by 0.02235 microVolts. The final term, 2^{23} is required because the Cyton board uses the ADS1299 chip, which is a 24-bit device, and outputs data in two’s complement format [9].

C. Signal Processing

Signal processing was a crucial step in designing our BCI. EEG signals are measured as by placing electrodes on the scalp and recording the voltage differences between them (Figure 1). This raw voltage reading includes significant noise. If left unfiltered, the noise masks nearly all the patterns a model could use classify signals.

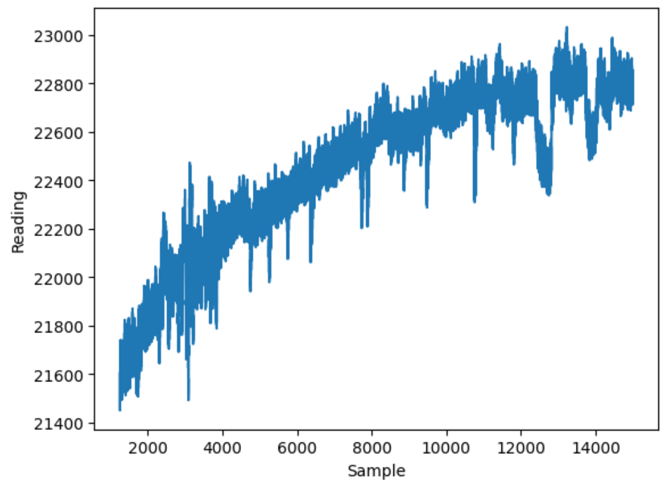

Fig. 1. Raw EEG data

Brain waves can be broken down by frequency (Figure 2), and motor signals dominantly reside in gamma (30hz+) waves. Therefore, signal processing techniques are applied to enhance the quality and extract meaningful features from the EEG signals.

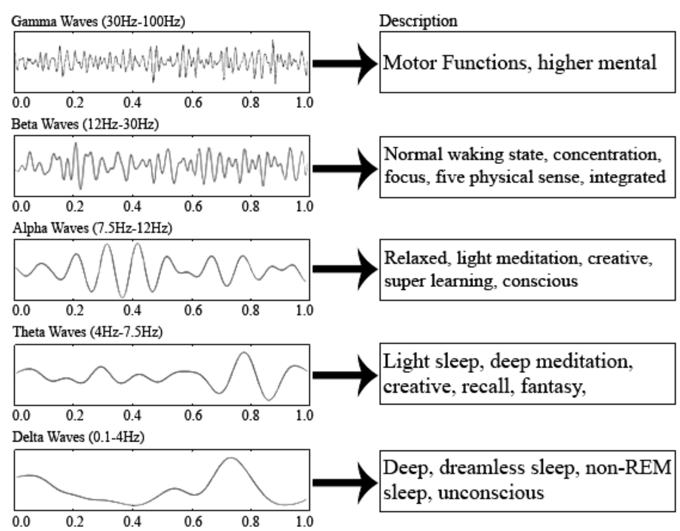

Fig. 2. Brain wave frequency ranges.

The first, and arguably most important, function applied is the Fourier transform, which decomposes signals into a sum

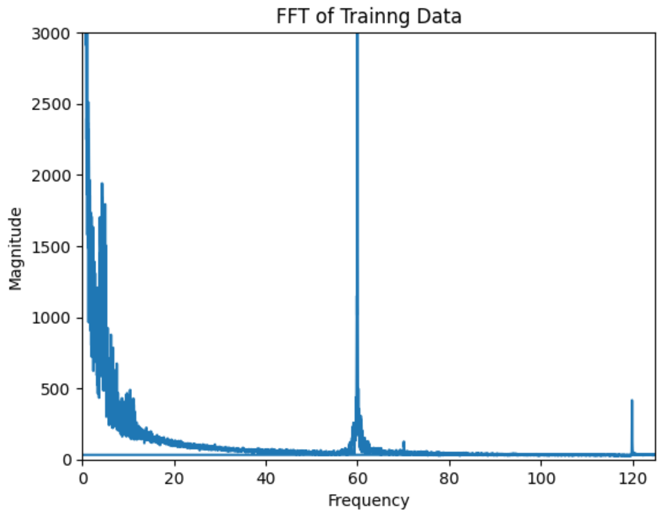

Fig. 3. Fourier transformed EEG data.

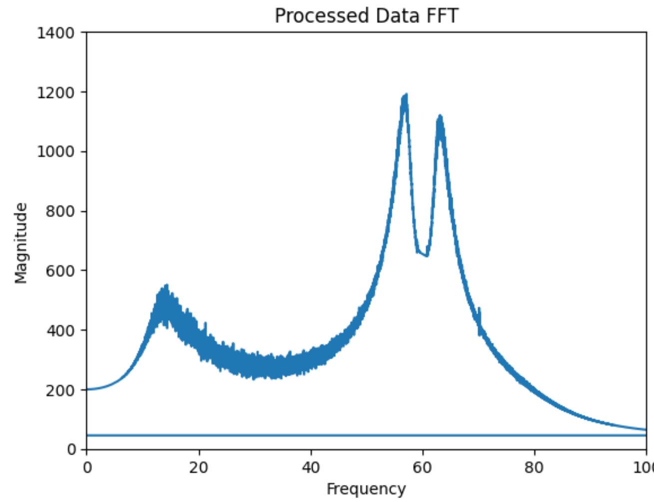

Fig. 4. Processed EEG data.

of overlapping sine waves of varying frequency. In practice we opted for `numpy`'s implementation of the fast Fourier transform (FFT) for its computational efficiency. By applying the FFT, one can identify the dominant frequencies or spectral components of the EEG signals, which reflect the different brain waves.

The result of applying the FFT to the raw signal is shown in Figure 3. In the plot there are three obvious spikes of noise, the most noticeable being the drastic spike at 60hz. This is caused by the background of AC power, which (in Canada) is 60hz. Also, as previously discussed, we are only concerned with signal in a certain frequency range. To address these issues, we apply a bandpass and a notch filter. The notch filter is a type of band stop filter that blocks a narrow band of frequencies, allowing all others to pass through. We applied this at 60hz with a notch size of 3, to knock out the AC power noise. The bandpass filter is used to filter for only the frequency range we care about: 13hz-80hz (i.e. filtering for only gamma and beta waves; while motor signals predominantly reside in gamma waves, empirically we found including beta waves gave better results). The filtered signal is shown in Figure 4.

A technique we experimented with but were unable to utilize effectively was band power, which quantifies how potent certain frequencies are within different ranges. Band power can be calculated by squaring the amplitude of each frequency component obtained by FFT. By measuring band power, one can compare the relative strength of different frequency bands across time or electrodes. Unfortunately, in this motor classification task band power didn't provide a useful feature and only degraded the performance of our models.

A final consideration for EEG signal processing is Nyquist frequency, which is the minimum sampling rate required to capture all the information in a signal without aliasing [10]. According to Nyquist theorem, one needs to sample at least twice as fast as the maximum frequency of interest. For EEG signals that range from 13 to 80hz, one needs to sample at least 120hz. However, since our EEG device has a higher sampling rate of 250hz this was not an issue for our BCI design.

D. Statistical Model

Due to the proximity of the eyes and related muscles to the brain, blinking produces a rapid voltage drop in the EEG data, shown in (Figure 5). This led us to trying a simple statistical classifier on the data. The classifier simply compares the rolling average signal strength of a 60 sample window to the average of the previous window. Because packets come in 255 sample bursts, we were able to run the classifier live with 4 windows to compare.

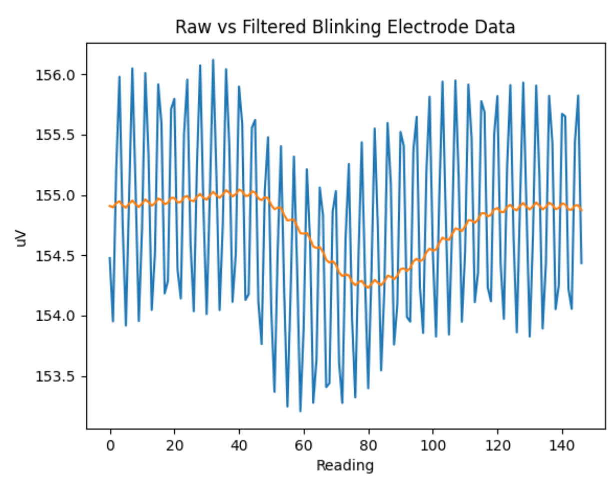

Fig. 5. Forehead electrode data recorded during a blink.

E. Convolutional Neural Network

The first ML model we built was a CNN based on the EEG-Net [7] architecture (Figure 6). We simplified the architecture, namely by reducing the convolutional layers from 2D to 1D in order to fit our collected data. This is composed of three convolutional layers, each with a kernel of 3 and immediately followed by batch normalization to stabilize training and add regularization helping the model to generalize. The second and third convolutional layers are followed with ELU activation, average pooling, and 25% dropout. Finally the outputs are passed through a fully connected layer with two outputs and softmax activation to give the prediction.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 3, 64)             192

 batch_normalization (BatchN  (None, 3, 64)            256
 ormalization)

 conv1d_1 (Conv1D)           (None, 3, 64)             12288

 batch_normalization_1 (Batc  (None, 3, 64)            256
 hNormalization)

 activation (Activation)     (None, 3, 64)             0

 average_pooling1d (AverageP  (None, 1, 64)            0
 ooling1D)

 dropout (Dropout)           (None, 1, 64)             0

 conv1d_2 (Conv1D)           (None, 1, 128)            24576

 batch_normalization_2 (Batc  (None, 1, 128)           512
 hNormalization)

 activation_1 (Activation)   (None, 1, 128)            0

 average_pooling1d_1 (Averag  (None, 1, 128)           0
 ePooling1D)

 dropout_1 (Dropout)         (None, 1, 128)            0

 flatten (Flatten)           (None, 128)               0

 dense (Dense)               (None, 2)                 258

 activation_2 (Activation)   (None, 2)                 0

=================================================================
Total params: 38,338
Trainable params: 37,826
Non-trainable params: 512
_________________________________________________________________
```

Fig. 6. CNN model architecture, based on EEGNet.

F. Singular Vector Machine

The second ML model was a support vector machine (SVM) utilizing time series data. A rolling moving average was applied to filter out high-frequency oscillations. Using smoothed data, the SVM was trained to identify the distinct trough shape shown in Figure 5. Performing a binary classification on time series data allows us to identify blinks occurring in real-time with high accuracy.

III. Results

TABLE I
Performance metrics of the classifiers.

Model	Accuracy	Precision	Recall	F1-Score
Statistical Classifier	81.36%	76.92%	57.97%	66.12%
CNN (overfit)	92.82%	93.42%	92.82%	92.80%
SVM	94.43%	92.85%	100%	96.30%

A. Statistical Model

The simple statistical classifier performed suprisingly well. It achieved an accuracy of 81.36%, and had very few false positives (only 5.45% of predictions). However, it noticeably lacked in its false negative rate at 13.18%. This high false negative rate is reflected in the low recall score of the model of 57.97%. In practice, this led to a relatively smooth gaming experience where the occasional input was missed but this was easily rectifiable by blinking again quickly. Along with good performance, this model had the added advantages of extremely quick prediction time and being entirely resilient to imbalanced data. This made it by far the quickest to build and had minimal impact on the performance (framerate) of the game.

B. Convolutional Neural Network

The CNN model had impressively good performance on validation data. It achieved 92.83% accuracy, and similarly high scores for all the other performance metrics. However, upon testing on data recorded on a different day, it was clear this model had severely overfit to its training data. On other datasets the model often had extremely high false negative rates (upwards of 90%) and was unusable other than briefly immediately after training.

C. Support Vector Machine

The SVM provided promising results across all metrics. Accuracy, recall, and F1 scores outperformed both the CNN and statistical classifier. The only metric in which SVM did not score highest was precision, in which the CNN outscored it by less than 1%. Furthermore, the model generalized well, identifying blinks with a cross-validation accuracy of 94.43%. Overall, the SVM provided strong results and generalization.

IV. Conclusion

We were successful in building an EEG BCI game controller. Of the models built, the SVM performed the best and both the SVM and statistical classifier worked as playable BCI control algorithms in practice. The CNN did not perform well or work in live testing due to a failure to generalize.

To effectively implement a CNN or other deep learning models, significantly larger datasets are required. Future steps for this project could include data collection across multiple people, spanning the course of several months. This process could mitigate the overfit observed in our trials and would provide a more generalizable model.

Future steps for this project include increased control complexity. Using different actions to provide several control options to the user would provide a more ergonomic interface. Within the scope of this EEG's capabilities, it could be possible to provide two control signals through winking the right and left eyes, and possibly another movement with the arms or legs. This three-input system may cause a decrease in performance, but would provide the user with higher utility when interfacing with a computer.

Many options are possible to increase the performance of the BCI. First, using wet electrodes provides more accurate data. When using dry electrodes, interference from the user's hair and skin oils adds increased noise to the signal. Wet electrodes apply a conductive gel to the user's skin, which mitigates these sources of error. Secondly, using a higher quantity of electrodes would provide more detailed data. Tasks such as motor imagery and thought recognition are achievable using higher resolutions EEGs, ranging from 16 to 256 electrodes [11]. Additionally, electrode locations can be customized to provide signals from desired parts of the brain. For example, many motor signals originate from the frontal lobe of the brain. Re-locating electrodes to provide higher density over the frontal cortex could provide better results for motor movement classification. Exact electrode locations could be chosen to meet the needs of the user and the task at hand.

In short, the results achieved from this BCI project were promising. The goal of controlling a single-input video game was achieved with high consistency. Investigation into different control signals and new EEG technology could provide a more immersive interface for the user, and the development of this technology will enable those with disabilities to interact with the world in a more effective manner.

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