2015

MODIFICATION AND EVALUATION OF A BRAIN COMPUTER INTERFACE SYSTEM TO DETECT MOTOR INTENTION

Christopher V. Hagerty-Hoff
Virginia Commonwealth University

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A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University

by

CHRISTOPHER HAGERTY-HOFF
B.A., the College of William and Mary, 2012

Director: OU BAI, PH.D.
Assistant Professor, Department of Biomedical Engineering

Virginia Commonwealth University

Richmond, Virginia

April, 2015

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1. Abstract

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Major Director: Ou Bai, Ph.D., Assistant Professor, Department of Biomedical Engineering

It is widely understood that neurons within the brain produce electrical activity, and electroencephalography—a technique used to measure biopotentials with electrodes placed upon the scalp—has been used to observe it. Today, scientists and engineers work to interface these electrical neural signals with computers and machines through the field of Brain-Computer Interfacing (BCI). BCI systems have the potential to greatly improve the quality of life of physically handicapped individuals by replacing or assisting missing or debilitated motor functions. This research thus aims to further improve the efficacy of the BCI based assistive technologies used to aid physically disabled individuals. This study deals with the testing and modification of a BCI system that uses the alpha and beta bands to detect motor intention by weighing online EEG output against a calibrated threshold.

2. Introduction

As modern assistive technology has become more sophisticated, transitioning from simple rigid objects intended to only help support the user's weight to mechatronic devices capable of complex reactive support and even motion, a burgeoning need for increased user control has arisen: now that the hardware is sufficiently advanced, research has shifted focus to technology that allows the wearer to communicate more easily with the device in order to modify or control its behavior. One of the foremost methods for interacting with these assistive devices is Brain-Computer Interfacing (BCI). This research focuses on the evaluation and modification of a BCI system capable of recognizing user motor intention and translating it into machine commands.

2.1 Electroencephalography and Brain Waves

Electroencephalography (EEG) is the technique of recording the firing of neurons in the brain using electrode arrays mounted on the scalp. These electrodes are sensitive to the electrical activity associated with the postsynaptic potentials of neurons in the cerebral cortex. It was Hans Berger, in 1922, who first measured the EEG waves in the human brain and coined their modern name [1]. The biopotentials recorded by EEG are products of localized depolarization/polarization across the brain as an electrochemical reaction following the release of neurotransmitters and the resulting change in membrane conductivity [2]. Specifically, these potentials are the sum of excitatory and inhibitory signals traveling through dendrites.

The electrodes mounted on the scalp have a standard sensitivity of 7 μV per millimeter, and the recorded data typically undergoes averaging techniques to represent the net potential measured in the target zone proximal to the electrode [3]. Electrode arrays are typically assembled upon the scalp in the "10-20" placement invented by Herbert Jasper in 1957 with the earlobe used as a reference voltage and aqueous gel as a medium [4]. This placement (*Figure 1*) is regarded as the international norm [5]. This orientation allows for standardized measurements of brain activity ordered by scalp locations corresponding to various parts of the brain.

When it comes to modern research, EEG is often used in experiments studying normal and abnormal neurophysiology. As EEG activity is very sensitive to a plethora of factors including various emotions, levels of alertness/drowsiness or mental/neural disorders, many researchers utilize the technique to observe different normative brain waves in subjects exposed to a variety of conditions or tasks as well as to examine the neural activity associated with diseases such as Alzheimer's, epilepsy or narcolepsy. Medical practitioners also use EEG to look for the markers associated with said disorders to assist in the diagnosis of their patients [6] [7].

A chronic problem that researchers using electroencephalography have had to deal with is that of electrode artifacts. These artifacts represent corruption of the desired EEG data and occur when the electrodes acquire signals from sources outside of the target area leading to the distortion of the original signal. Artifacts in EEG are commonly caused by unwanted electrooculography (EOG)—electrical activity that occurs during eye movement as a result of polarity differences between the front and back of the eye—or electromyography (EMG)—motoneuron activity that can be detected during muscle contraction [5] [6]. In EEG, often the source of these artifacts is EOG and blinking, but it is not uncommon for neck or scalp muscle contraction to throw off data recording. Additionally, a "slip" or any form of insufficient contact between the scalp and the electrodes will also produce artifacts [7]. These artifacts can typically be dealt with using digital filtering or other post-processing techniques.

Regarding EEG waves, there are several different oscillatory brain signals ordered by the frequency band in which they occur (Table 1). The structure and behavior of these rhythms depends on the relative abundance of excitatory and inhibitory connections between neural masses [2] as well as the activity and health of the brain [8]. Two of the most important waves are the alpha and beta rhythms. The alpha rhythm is a very strong waveform that predominately originates from the occipital lobe of the brain. The alpha rhythm amplitude is strongest during periods of wakeful rest when the subject's eyes are closed, in which state the alpha rhythm has the largest amplitude among the other brainwaves. The behavior of the alpha rhythm historically have been associated with activity in the visual cortex, but more recent work has suggested that it plays a role in coordination and communication across the neural network [9].

The beta rhythm has a much broader frequency band than the alpha (as can be seen in *Table 1*) and as such is divided into three sections: Low Beta Waves (13-16 Hz); Beta Waves (16.5-20 Hz); and High Beta Waves (20.5-30 Hz). These are also referred to as “Beta 1,” “Beta 2” and “Beta 3” powers respectively [10]. Beta wave activity and strength is often associated with alertness and consciousness with various amplitudes and frequencies being associated with different levels of concentration [11]. Additionally, beta waves in the motor cortex are associated with isotonic muscle contraction, and during movement changes/transitions, these waves have been observed to be suppressed [12]. When the strength of these waves is artificially amplified (induced by transcranial alternating-current stimulation) an increase in isotonic muscular activity can be observed causing a retardation of motor movement [12].

Another pattern heavily related to the motor cortex is the sensorimotor rhythm (SMR) (*Figure 2*), a waveform occurring within the upper frequency band of the alpha rhythm. The SMR displays distinct patterns of behavior during the activation of sensory-motor areas of the brain. During states of inactivity/immobility, the SMR has a high amplitude, but when the appropriate sensory or motor areas are activated, the amplitude of the SMR drops. This behavior can be produced during muscle movement or even with motor imagery [13].

2.2 Brain-Computer Interfacing

The purpose of brain-computer interfacing (BCI) is to create a system that allows a machine to be affected or even controlled by the user's brainwaves. Typically, there are two types of BCI systems (*Figure* 3): “open loop” where a system responds to user input with no feedback; and “closed loop” where a system provides reactive feedback to user input. Initial studies were focused on animals—monkeys in particular—yielding results that illustrated the extent of the brain's plasticity and its ability to adapt to new stimuli and to focus upon the activation of specific zones of the motor cortex [14]. Through these studies, researchers were able to design algorithms capable of interpreting an animal subject's raw neural data. This would then allow engineers to coordinate patterns in the neural activity with commands to be delivered to a mechatronic device [15] [16].

In the early incarnations of the technology, these interfaces were based on invasive EEG systems featuring percutaneous electrode arrays. While these systems enjoy a higher overall resolution than non-invasive systems, the disadvantages outweigh the advantages (when its purpose is solely to gather data): these invasive systems introduce a major risk of serious bacterial infection at the site of implantation which can easily lead to life-threatening meningitis. Additionally, the electrode artifacts that are inherent in non-invasive systems (which supposedly were not present in invasive systems—or so researchers theorized) are also common in the invasive systems [17] [18]. Coupled with the danger and inconvenience of surgery, most modern BCI research and technologies rely upon non-invasive systems.

Magnetoencephalography, magnetic resonance imaging, electrocorticography and EEG are the non-invasive (though electrocorticography is partially invasive) technologies typically used to record the activity of the brain for BCI [19]. EEG in particular is well suited for BCI technology due to its high temporal resolution, simplicity and portability. As discussed previously, non-invasive EEG suffers from noise and artifact susceptibility as well as poor signal resolution. Additionally, surface electrodes can only pick up signals at the surface of the brain; non-invasive EEG cannot be used to capture signals from deeper within the brain [18]. Regardless, the bulk of brain-computer interfaces rely on non-invasive EEG. The idea of using EEG waves as input for BCI is an old one but only recently have engineers managed to successfully implement this concept [19]. The typical EEG-BCI follows a particular paradigm of collecting EEG data, processing it, translating the processed data into commands delivered to an output system and providing a feedback element to the subject (*Figure 4*). Recording raw data from the brain is simple, but analyzing this data and recognizing the features/patterns critical to the experiment has been the major crux of BCI technology. Feature extraction entails separating useful EEG data from undesired signal noise/artifacts while simplifying the data such that it becomes possible to decipher the meaning within the signal, classify it and translate it to the output device. There are several algorithmic methods used to process raw EEG data including Hjorth parameters, wavelet transforms, Fourier transforms and digital filtering. As for classification algorithms, there are several descriptive categories a classifier may all into (*Table 2*) [20].

- **Generative-discriminative:** Generative classifiers (e.g., Bayes quadratic) compute the likelihood of each class and choose the most probable candidate, while discriminate classifiers (e.g., Support Vector Machines) only discern class membership in order to directly classify a feature [21] [22].
- **Static-dynamic:** Static classifiers (e.g., MultiLayer Perceptrons) do not take temporal information into account during classification: they classify a single

	feature vector. Dynamic classifiers (e.g., Hidden Markov Models) classify a sequence of feature vectors thus allowing for the modeling of temporal behavior [23].
• **Stable-unstable:**	Stable classifiers (e.g., Linear Discriminant Analysis), have low complexity/capacity. They are said to be stable as small variations in the training set do not considerably affect their performance. Unstable classifiers (e.,g., MultiLayer Perceptron) have high complexity. Small variations of the training set may lead to important changes in performance [24].
• **Regularized:**	Regulariation consists in controlling the complexity of a classifier in order to prevent overtraining. A regularized classifier has good generalization performances and is more robust with respect to outlying patterns [25] [26].

Table 1: Types of Classifying Methods for BCI

As for the features themselves, there is a broad spectrum of elements that engineers have attempted to incorporate into BCI systems including: EEG amplitude [27]; Band Powers; Power Spectral Density [28]; AutoRegressive parameters [29]; time-frequency features [30]; and inverse model-based features [31]. Additionally, there are several other parameters and properties that must be considered when designing the feature extraction system (*Table 3*) [19] [20] [21].

• **Noise and outliers:**	BCI features are noisy or contain outliers because EEG signals have poor signal-to-noise ratio.
• **High dimensionality:**	In BCI systems, feature vectors are often of high dimensionality [32].

	Several features are generally extracted from several channels and time segments before being concatenated into a single feature vector.
• **Time information:**	BCI features should contain time information as brain activity patterns are typically related to specific EEG time variations.
• **Non-stationary:**	BCI features are non-stationary since EEG signals may rapidly vary over time and between sessions.
• **Small training sets:**	Training sets are relatively small, since the training process is both time consuming and demanding for BCI subjects.

Table 2: BCI Properties for Feature Extraction

Particular time-variations of EEG across specific frequency bands are used for BCI. As such, the time course of these signals must be considered during the design of the BCI system: this data will be vital in the feature extraction stage of the BCI [21] [33]. Accordingly, researchers typically follow one of three different approaches: concatenation of features from different time segments (extracting features from different time segments and concatenating them into a single feature vector)[34]; combining classifications at different time segments (performing the feature extraction stage on multiple time segments and then combining the results) [35]; dynamic classification (extracting features from several time segments to build a sequence of feature vectors)[34] [36]. The method used most commonly is the concatenation of features across several time segments.

Once features are extracted and classified, output devices can be given a predefined set of instructions and a proportional feedback signal can be given to the user [21] [35]. Feedback is vital to BCI systems; it provides information for users that allows them to better learn, isolate and control the mental imagery/behavior to be classified for operation of the output device. This feedback signal can be visual or auditory in nature, and some systems even applies haptic/tactile technology to this end [37].

Overall, BCI systems generally fall into two categories: synchronous and asynchronous. In synchronous BCI systems, every feature of the signal is extracted and then processed in sequence. Once the first instruction is completed, the system will then process a new set of features [38] [39]. The subject is directed along a repetitive scheme to switch from one mental task to the next. This cue-based (occasionally called "cue-ball" [37]) thus features time-locked EEG phenomena, where a cue is given to the subject to provide a sequence of very specific input over a specific time interval: these intervals are often called "trials," which typically are 4-10 seconds in duration [40]. Asynchronous BCI systems, however, are more dynamic.

The asynchronous system can accept and process features one after another without waiting for the first instruction to be completed: the subject makes voluntary decisions on when to initiate mental tasks. For this reason, asynchronous BCI is often referred to as "self-paced" [37] [41]. Because of this, asynchronous BCI systems require continuous analysis of EEG input. This is to ascertain if the subject is in an Intentional Control State (IC): if the user is producing the correct input brain activity to trigger the BCI to send the predesignated command to the output device [39] [37].

The major difference between synchronous and asynchronous BCI systems is in their utility. Synchronous systems are ideal for research/analysis purposes, as it provides a model for a target brain-activity in a controlled environment. Asynchronous systems, more geared towards practical BCI devices, would be much less organized for data-analysis, but is far more adaptable and allows the user complete control over the system [37] [38]. Using the two systems in conjunction allows the researcher to calibrate the system for the subject by using a synchronous calibration program, maximizing the accuracy and efficacy of the following asynchronous trials by passing recorded parameters that will help in the feature extraction/classification process of the subject's brain waves [40].

The output device of the BCI can be as simple as a computer cursor or as complex as a robotic arm. Some researchers are even exploring the utilization of BCI in computer and video game control [41]. A BCI system can be designed to interact with any electrical technology, but the output device that this research focuses upon is an above-the-knee prosthetic leg system.

The specific aim of this study is to modify a BCI system designed to detect a subject's motor intentions in order to increase its accuracy and then to evaluate its performance. This was done by testing the system in online synchronous trials using the original system and the modified system before performing post-processing to run offline tests to directly compare the accuracy of the old system versus the new system.

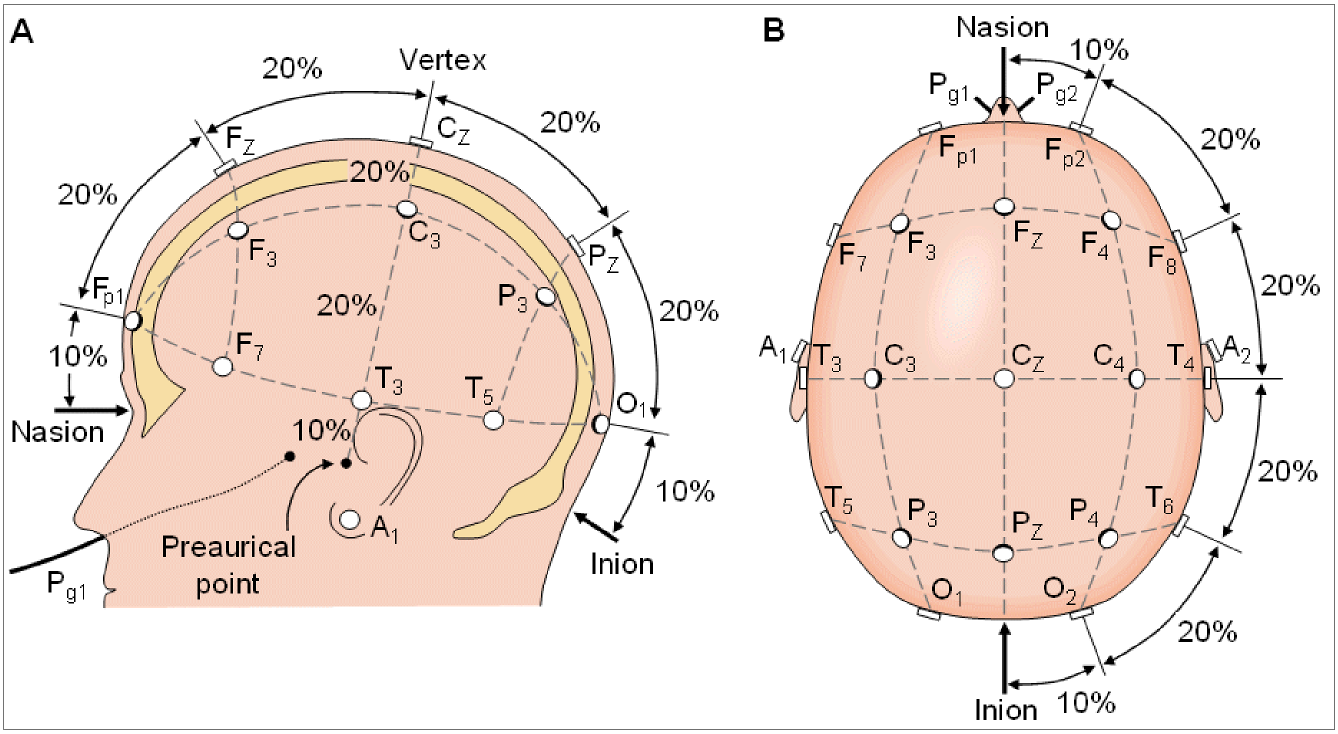

Figure 1: 10-20 International Electrode Placement System [www.bci2000.org]

Band	**Frequency**
Delta	1-4 Hz
Theta	4-7 Hz
Alpha	~7-13 Hz
Beta	~13-30 Hz
Gamma	30+ Hz

Table 3: Standard EEG Bands and Associated Frequencies

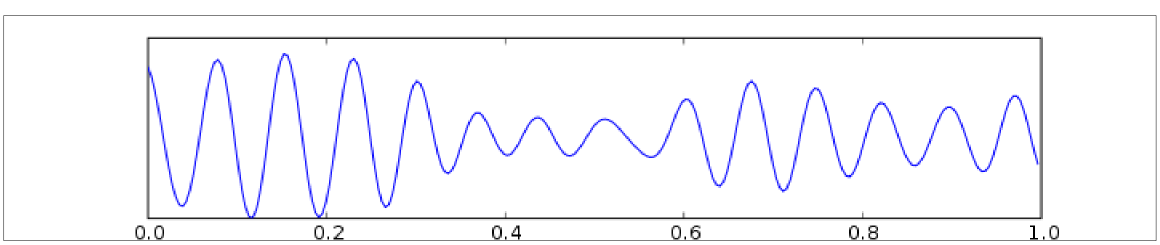

Figure 2: Sensorimotor Rhythm in Action, Energy vs Time) [Hugo Gamboza Dez 2005]

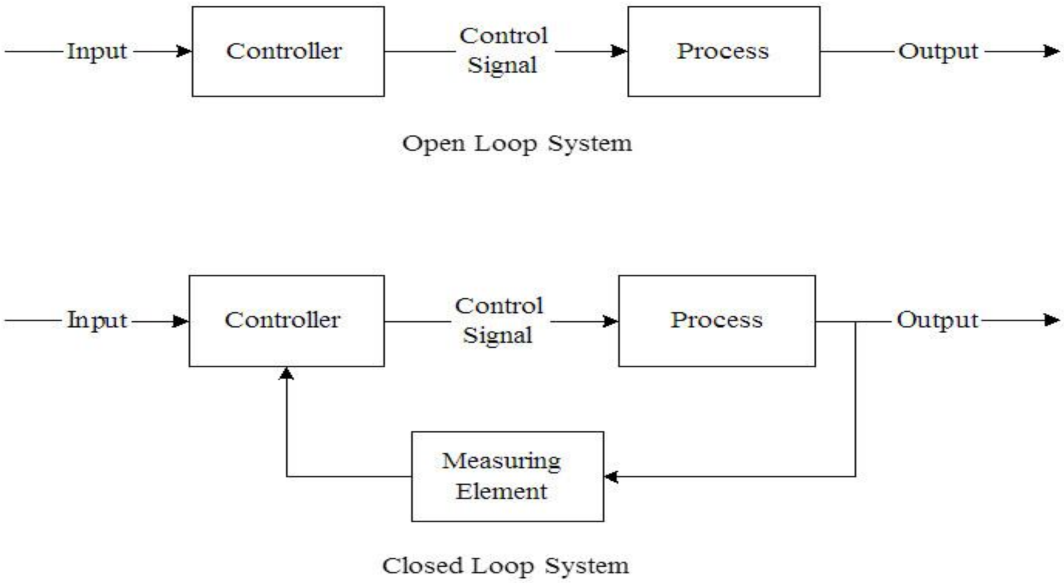

Figure 3: Comparison of Closed and Open Loops [www.micromo.com]

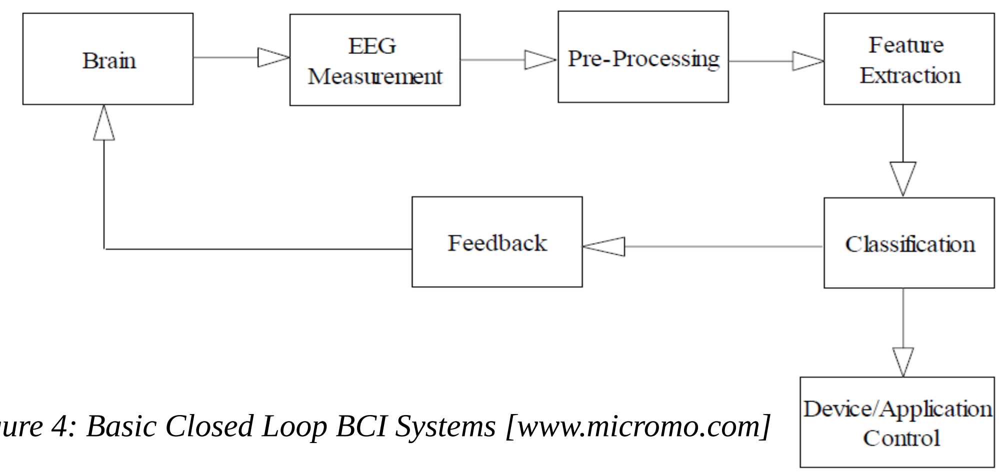

Figure 4: Basic Closed Loop BCI Systems [www.micromo.com]

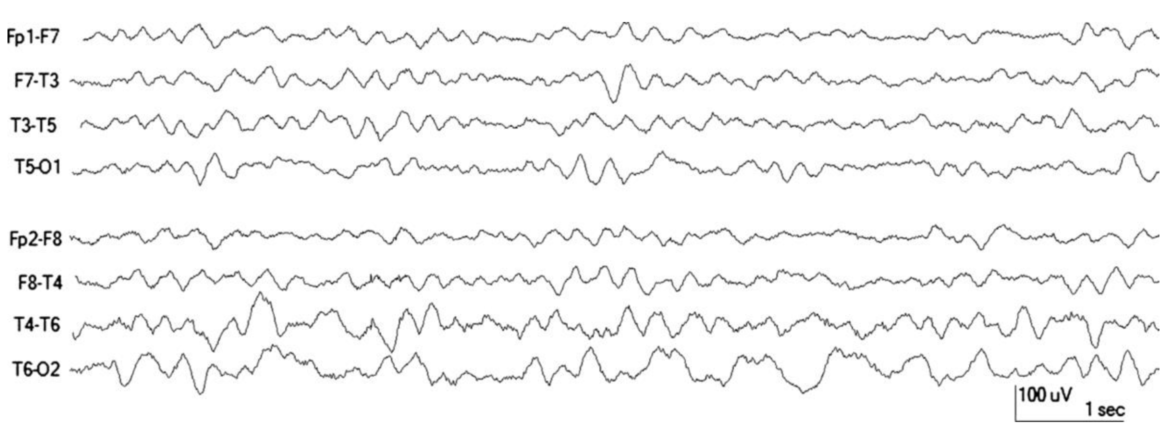

Figure 5: Sample EEG Data [Sample Data from EEG Lab Matlab Toolbox]

3. Methodology

The experiment and the ensuing research consisted of several devices and programs. Before going into each part of the methodology, here is a simplified overview of the methodology involved in this work prior to the post-test processing.

- EEG system is set up, connecting the subject to the amplifier.
- The amplifier is connected wirelessly to the investigator's laptop via Bluetooth.
- The calibration program is run to identify the proper thresholds.
- Calibration data is passed to the detection program which is then run to test system accuracy.

3.1 EEG System

The EEG system features seven electrodes across the central nodes (*Figure 6*) placed against the head using either a headband or an EEG cap (both were used in this experiment); this placement is based on the 10/20 128 electrode system. A conductive gel was used as a medium between the electrodes and the scalp to reduce the effects of skin impedance. Electrodes are attached to the earlobe to provide a reference voltage. Finally, the ends of these leads are then plugged into the amplifier.

3.2 The Amplifier

The amplifier used in this experiment is the Texas-Instruments ADS1299 (*Figure 7*), a low-noise, 8-channel, 24-bit analog front-end for biopotentials designed to be used with EEG and ECG. It features eight low-noise PGAs with high resolution simultaneous sampling. It has a very low input-referred noise at 1.0 μVpp (70-Hz BW). It has a power of 5 mW/channel and an input bias current of 300 pA. The data rate is 250 SPS to 16 kSPS. Finally, the device has a CMRR of 110 dB. The amplifier is programmed for an overall gain of 8000. The amplifier was then wirelessly connected to the investigator's laptop using Bluetooth and interfaced with Dr. Ou Bai's BCI2VR Matlab toolbox, a BCI system with virtual reality simulations intended for similar experiments. Several rounds of data-collecting were performed upon various subjects to test the connectivity between the laptop and the amplifier.

3.3 The Calibration Module

Before subject volition can be accurately recorded, Dr. Bai's system must be properly calibrated. The purpose of the calibration module is to observe the brain waves of the subject in time frames corresponding to motor imagery and relaxation in order to find the threshold parameters to be used for volition recognition. This is done by a synchronous test where the subject, connected to the EEG-BCI system made up of the EEG, amplifier and laptop, is given visual and audio cues to either begin to imagine motor control or to just relax. The raw data was sampled at 250 Hz . Originally, the alpha band is observed using a bandpass filter (*Figure 8*) though in later trials, the beta band is observed instead. After several trials (20-40) the average value of the resting threshold and the volition threshold are computed and recorded. These values are then exported to a calibration file which will then be passed to the detection module.

3.4 The Detection Module

Once the calibration is complete, the accuracy of the system and the calibration configuration is tested using the detection module. Like the calibration module, this program is a synchronous BCI test where the user is given visual and audio cues that correspond to periods of mental motor imagery and rest. Unlike the calibration system, the detection module weighs the online recorded EEG power against a threshold value defined by the user's calibration profile (the average of the resting and the active thresholds recorded during the calibration). If the power output of the signal drops below the threshold (within a configurable sensitivity) during an “action” step, this is recorded as a true positive. If it drops below the threshold during a “relax” step, this is recorded as a false positive. Likewise, if the power output remains above the threshold during a “relax” step, this is recorded as a true negative, and if it remains above the threshold during an “action” step, this is recorded as a false negative. This approach varies from traditional BCI systems which typically require the subject to modulate their brain activity in some abnormal fashion; instead—if successful—the program allows for subjects to organically control the system by their thoughts. The accuracy of the system is measured at the end of all trials through weighing the number of true positives and true negatives against false positives and false negatives, where **ACC** is the accuracy, **TP** is the number of true positives, **TN** the number of true negatives, and **X** the total number of positives and negatives both true and false:

$$ACC = (TP + TN) / X$$

Finally, the subject is provided visual feedback as he completes the trials, a bar with a cursor that rises and falls in sequence with their EEG signal power output. The threshold is also shown as a static bar, allowing the subject to see how close or far he is from a successful activation.

3.5 Post-Processing

Post-processing was done after several trials using the alpha rhythm for the calibration and detection modules that yielded poor accuracy. First, the electrode headband was swapped out for a traditional EEG cap. This did not result in any numerically significant difference. Next, the alpha band was removed from the equation in order to focus upon the beta band with a bandpass of 13-30 Hz (*Figure 9*). When the results of this were promising, the earlier results were revisited. The offline detection data and the corresponding calibration profiles were used to re-examine the earlier tests to see if they were more accurate under the new configuration. Like the original, this program processes data in three second steps with a sampling rate of 250 Hz for a total number of 750 samples. The modified functions (see appendix) used are as similar to the original program as possible to ensure that the results of the tests will be as close as possible to an online equivalent. The pre-recorded data is run through the offline program which then filters out everything outside the beta band and compares the data against the thresholds passed on by the calibration profile. The same algorithms are used to detect and record the number of true/false positives and true/false negatives. Finally, the accuracy of the new trial is calculated using the formula:

$$ACC = (TP + TN) / X$$

The data is then returned in a multidimensional array consisting of the original signal in the structure **N** x 7 x 750 for a trial with **N** epochs / steps (the 7 corresponds to the number of channels to average and the 750 corresponds to the number of samples per channel in each epoch), the filter used to process the signal (in this case always the beta bandpass filter shown in *Figure* 9) and the calculated accuracy.

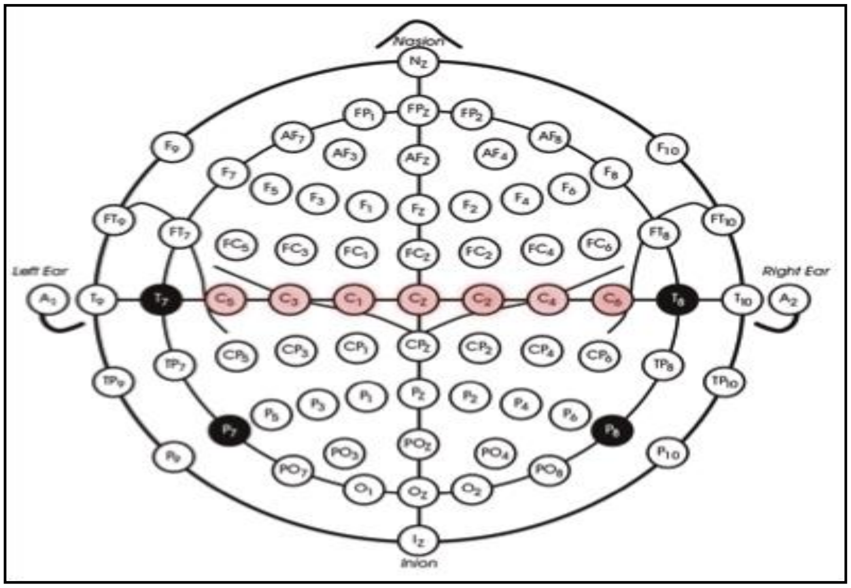

Figure 6: Electrode Distribution (in red)

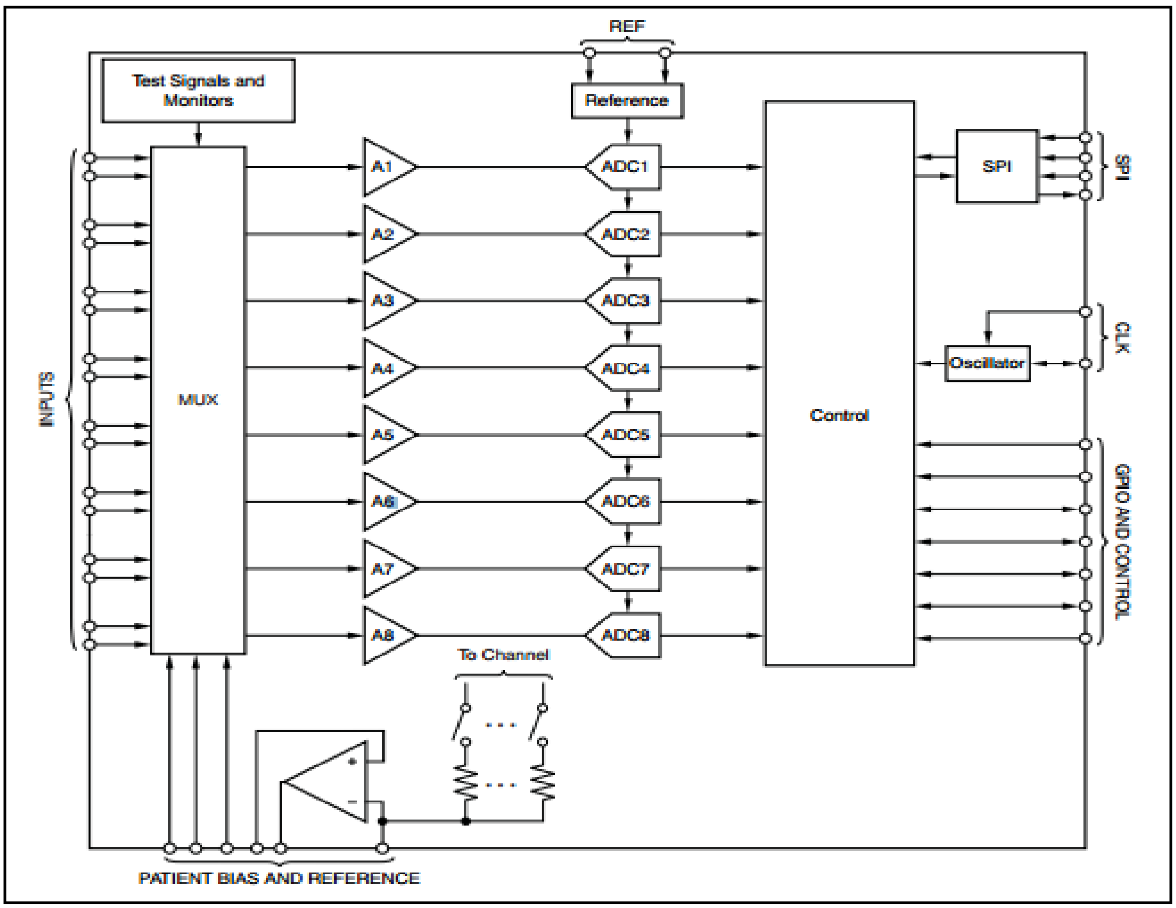

Figure 7: TI ADS1299 Diagram [Texas Instruments]

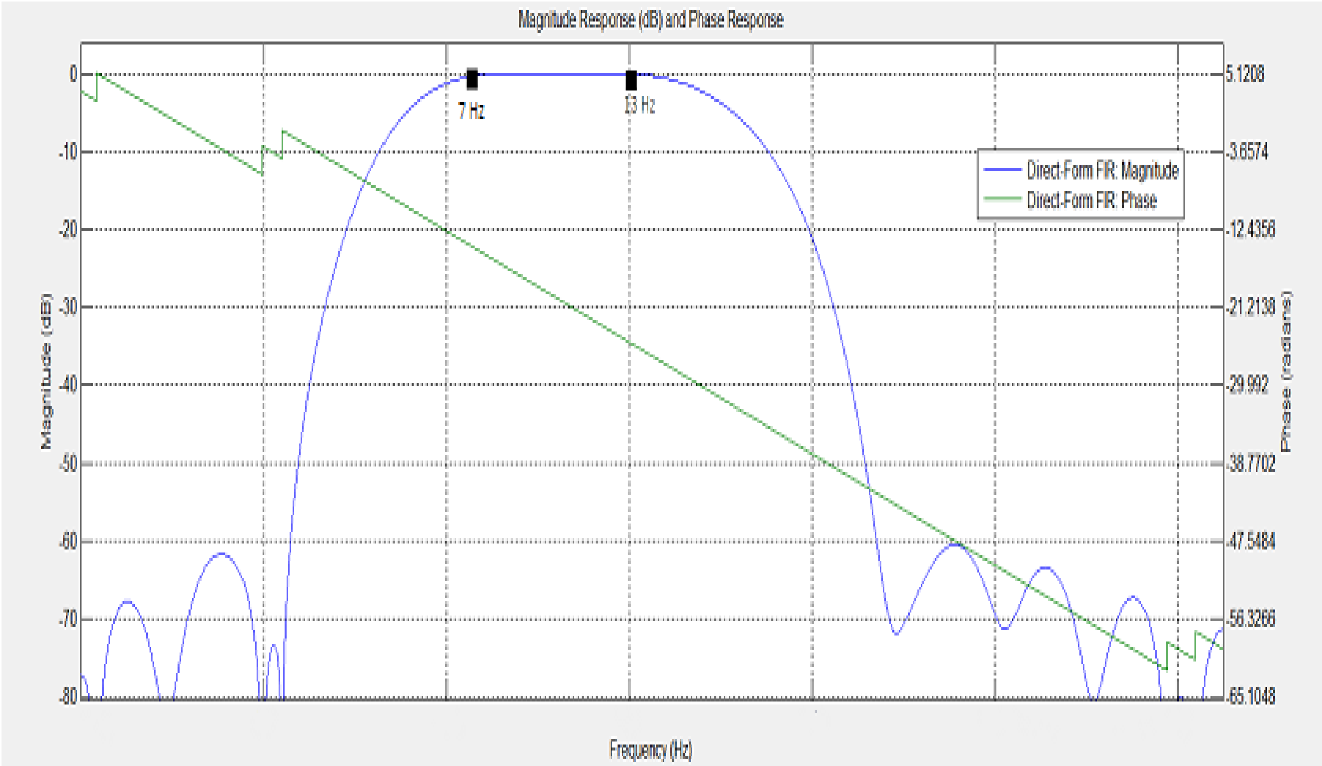

Figure 8: Alpha Band, Magnitude (dB) / Phase (radians) vs. Frequency (Hz)

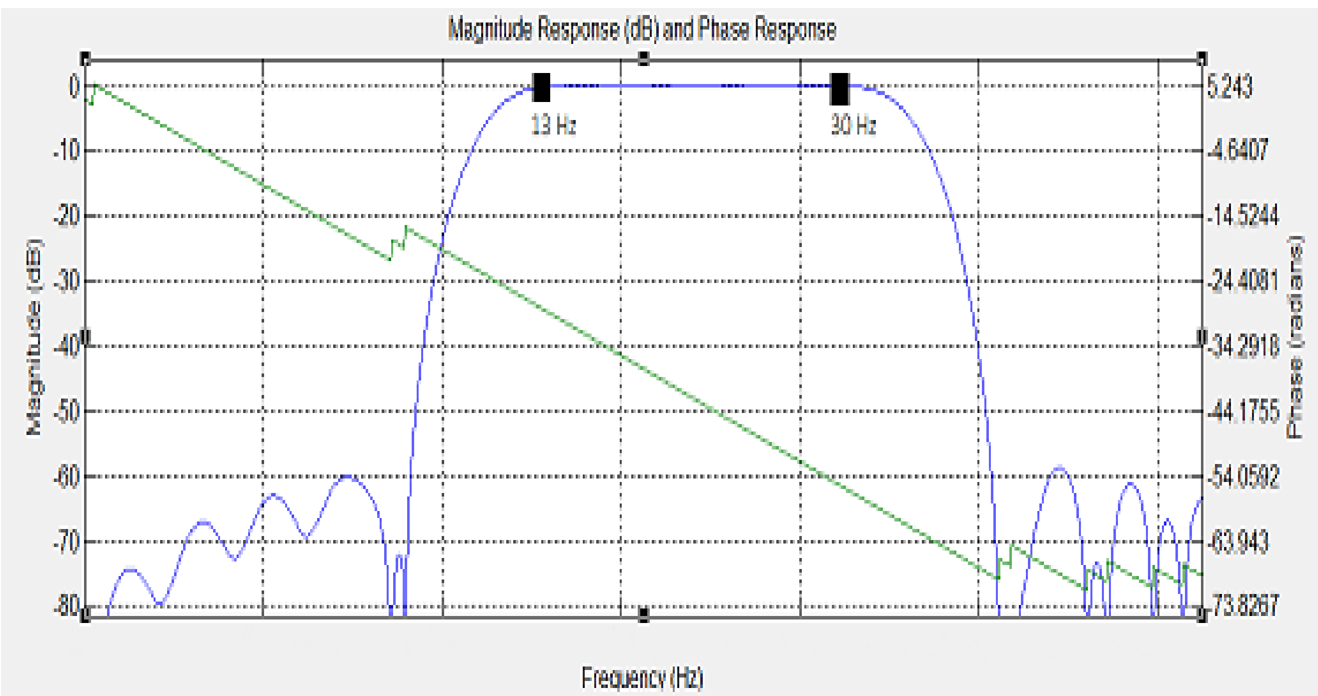

Figure 9: Beta Band, Magnitude (dB) / Phase (radians) vs Frequency (Hz)

4. Results

The results of the experiment can be broken into two sections. The first deals with the online testing of data collected both first-hand in the VCU EEG-BCI lab and second-hand from a concurrent experiment run by Dr. Bai and the McGuire Veteran's Hospital in Richmond, Virginia. The second section covers the post-processing of this data.

4.1 Online Testing

The results of the online testing using the validation system was as follows:

Test	Calculated Accuracy
Detection 1 – Subject 1	55.89%
Detection 2 – Subject 1	43.51%

Table 4: April 18th, 2014, Subject 1

This was some initial testing done on April 18, 2014, with the subject in question being the investigator. This demonstrated the functionality of the system and was what brought attention to the poor accuracy rate of the system. Several attempts to improve the accuracy by changing the configuration of the program were made (detection threshold sensitivity, and on April 21, 2014, more tests were run.

Test	Calculated Accuracy
Detection 1 – Subject 1	66.10%
Detection 2 – Subject 1	40.28%
Detection 3 – Subject 1	88.40% (Beta)

Table 5: April 21st, 2014, Subject 1

As can be seen, there was little improvement between the two tests and the previous set. Both of these short sets of tests were performed with the alpha band included in the experiment. Observation of the feedback in the closed synchronous BCI system prompted the investigator to remove the alpha band and focus on the beta band. Detection 3 on this set showed significant improvement, showing considerable potential for this technique.

The following set of experiments on April 22, 2014 (again using only the beta band, but this time including the primary investigator as well as the investigator) yielded these results:

Test	Calculated Accuracy
Detection 1 – Subject 1	81.20%
Detection 2 – Subject 1	80.26%

Table 6: April 22st, 2014, Subject 1

These results seemed quite promising given the high accuracy rate. This prompted the investigator to design the offline algorithm to test the accuracy from previous experiments using the alpha band. Before this was done, however, another set of trials were run on April 23rd, 2014 in a different experiment run by Dr. Ou Bai. The data was used in this study second hand without the inclusion of any identifying information. These were more extensive and cast doubt upon the beta band theory.

Test	Calculated Accuracy
Detection 1 – Subject 2	75.90%
Detection 2 – Subject 2	63.10%
Detection 3 – Subject 2	41.14%
Detection 4 – Subject 2	33.06%
Detection 5 – Subject 2	38.30%
Detection 6 – Subject 2	24.80%
Detection 7 – Subject 2	19.12%
Detection 8 – Subject 2	22.91%
Detection 9 – Subject 2	31.75%
Detection 10 – Subject 2	44.30%
Detection 11 – Subject 2	16.22%
Detection 12 – Subject 2	7.20%

Table 7: April 23rd, 2014, Subject 2

These results seemed bizarre and anomalous. There is an obvious decline in accuracy, followed by a brief rise and a subsequent drop (modeled in *Figure* 10). Detection 12 used 50 trials as opposed to the typical 30 trials.

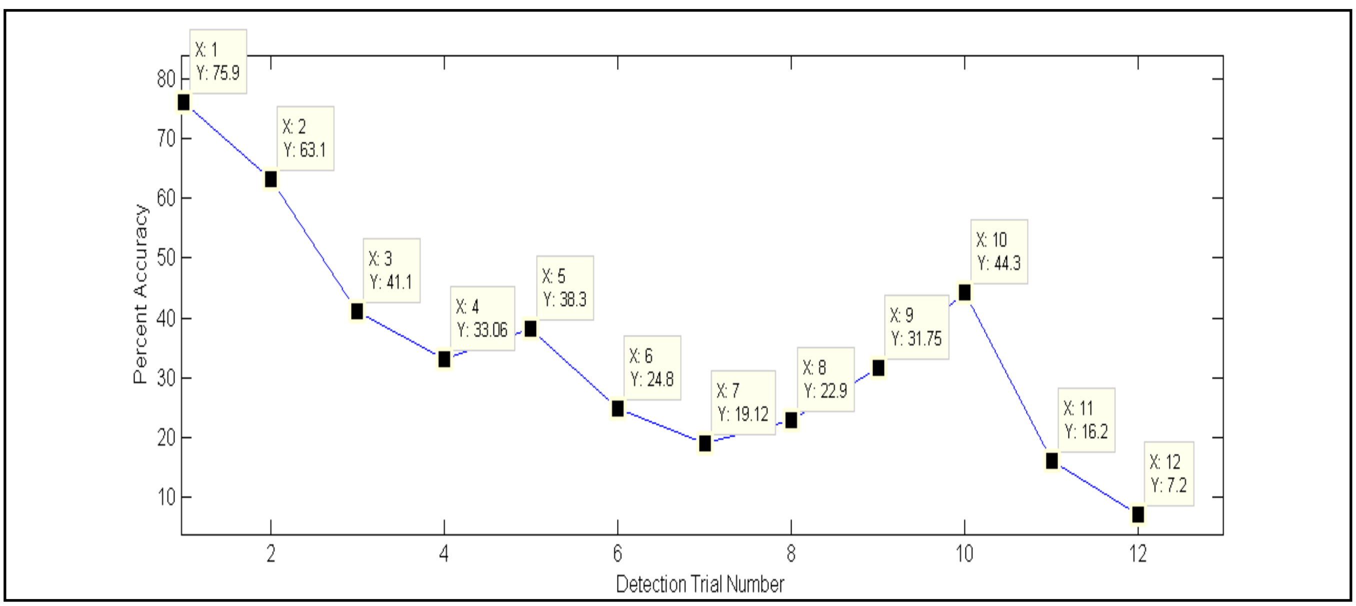

Figure 10: Accuracy Variability Across April 23rd Trials

This prompted further analysis of the system. Initially the investigator believed there might be electromagnetic interference from nearby machinery, but as there was no electrical activity present that had not been present previously, this theory was discarded. Next, the raw EEG was studied. Other than typical issues such as baseline wander and noise (both of which would have been eliminated by the filter), there was a peculiar artifact present (*Figure* 11). An electrical impulse was present across several channels. This was clearly not physiological, given the artifact's huge size. It was most likely caused by a packet loss during the wireless communication between the amplifier and the laptop. This is a behavior inherent in wireless connections, and given the algorithms and filters used in the experiment, it could not have impacted system performance significantly. Besides this, the EEG did not seem to exhibit any unusual traits or behavior, i.e. the signal acquisition was working as intended.

4.2 Offline Testing

To further test if motor intention could be reliably detected using the beta-band, the offline detection program described in the methodology was designed. The objective of this part of the experiment was to revisit the earlier data collected using the original bandpass and see if the accuracy of the system was affected significantly by the new system. Given the promising results of the last trial on April 21 and the trials on April 22, the investigator expected significant improvement to the prior data.

Test	Original Accuracy	New Accuracy
April 18 – Detection 1	55.89%	60.28%
April 18 – Detection 2	43.51%	40.92%
April 21 – Detection 1	66.10%	65.57%
April 21 – Detection 2	40.28%	43.19%

Table 8: Offline Testing Revisited Using the Beta-band

Despite the researcher's expectations, changing the bandpass of the filter did not have an appreciable effect upon the earlier data. There was neither a distinct positive or negative bias in the accuracy changes. With more data, perhaps one could be determined, but this data does not support the investigator's theory of the beta band being the optimal signal target for this experiment.

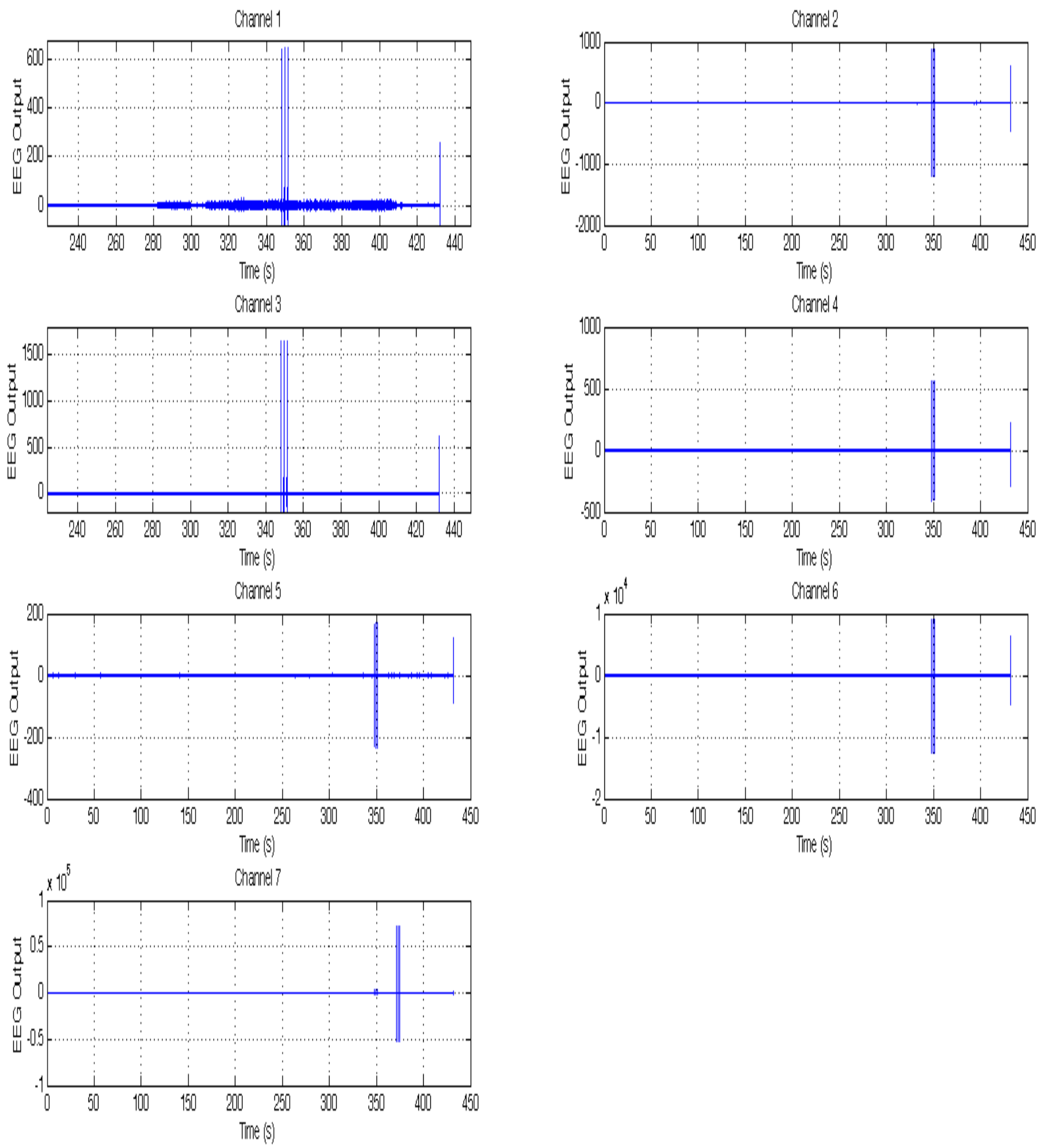

Figure 11: Complete EEG signal (Volts vs. Time) -- Subject 1 (Investigator and Author)

5 Discussion

5.1 Online and Offline Results and Research Direction

The online testing using the alpha band exhibited low accuracy across both sets of trials. The average accuracy of the experiments on the 18th was 49.7%, and the average of the experiments on the 21st was 53.19%. The overall accuracy of the system across these two days of testing was 51.45%. For reference, some BCI studies that enjoy higher accuracy during online testing (for activities such as driving a motorized wheelchair) report accuracies often in the range of 70-80% [42] [43].

When the beta band was the only signal used in the test, initial results seemed to exhibit high accuracy. With the three complete detection tests across two days, the average accuracy of the initial tests was 83.29%. This is a promising figure that initially suggested the system would be appropriate for use in motor related activities requiring precision and effective real-time processing. When the new algorithm was tested extensively, however, it became apparent that the alpha/beta change did not fully address the low accuracy issue (if it even did address it at all).

The tests that were run on the 23rd started out promising, but as experiments went on, the accuracy of the system steadily dropped. Overall, the average accuracy of the system was 31.63%. The accuracy variability of the testing on this day has been plotted out in Figure 10, illustrating this trend. This odd trend seemed to indicate that the more extensive the synchronous testing, the lower the accuracy. It is possible that there may have been some persistent technical issue affecting the results of the study, but if so, the investigator was unable to identify it. Alternatively, there may have been a physiological phenomenon interfering with the signal, the extra information overlaying on the target and leading to an increase in neural activity.

Another possibility is that the beta activity unique to each subject may or may not be ideal for this algorithm depending on the individual. This is certainly true for the SMR (sensorimotor rhythm) which has been observed to exist in different frequency ranges for different individuals (within a deviation of 1-5 Hz typically). However, it is important to note that the accuracy for the first two tests were over 70% and 60% respectively: they had a fairly high success rate, especially when compared to the following trials. It may be possible that the first two were anomalous, but given the nature of the subject as well as the clearly identifiable trend indicated in Figure 10, this seems unlikely.

The offline results, which the investigator had hoped would hold significant improvement over the prior work using the alpha band, did not show a distinct increase or decrease in accuracy when the target signal was processed using the beta band. The average accuracy of the original system was 51.45% and the accuracy of new system was 52.49%, with an increase of 1.04%—not a significant difference. This would thus suggest one of two possibilities: that the shift from the alpha to beta bands likely did not confer any increase in accuracy, and a different factor was responsible for the increased accuracy; or that a neurophysiological phenomenon (such as described in the previous paragraph) interfered with the earlier tests. The investigator finds the second theory more plausible (and more appealing) as while there were far fewer trials in the earlier days of testing, every day of testing (excluding the 22nd, where each subject tested only underwent one trial), there is a noticeable decrease in accuracy between the first and second trial.

The investigator's new hypothesis is that the low accuracy of the system is caused a concurrent neural process that can be observed during—or may even be provoked by—part of the online synchronous testing. Further research could be done to test this theory and, assuming it is true, identify this signal and a way to circumvent this issue to achieve accurate motor intention detection.

5.2 Future Direction of Technology

This kind of technology—interfaces that allow for the interpretation and detection of motor commands rapidly and in real time—would lead to significant advances in biomechatronic assistive technology. Historically, devices such as wheelchairs and prosthetic limbs have been stiff, non-responsive devices that rely purely on mechanical interaction for their operation. Today, significant advances have been made such that these devices are often mechatronic in nature: many modern wheelchairs are motorized and can be controlled by a joystick; many modern prosthetic limbs have biomimetic functions that the wearer can control to some extent albeit limited by unwieldy interfaces.

A system that observes the user's brain activity and recognizes when they are initiating a certain action (flexing of the hand or foot, for example) would allow for intuitive control over modern devices. Today, a man with no arms can use modern prosthetics and his shoulder muscles to slowly and carefully grasp a glass of water and bring it to his lips. Tomorrow, that man could use an interface like this one to perform the same action using only his thoughts. Years from now, using technology like this—and a sophisticated prosthetic limb—that man might be able to play the piano. Future work in brain computer interfacing may lead to great advances in assistive technology by establishing a software framework for controlling future devices. In the meantime, a concurrent study has used this system to attempt to connect the function of a BioM prosthetic leg—a biomechatronic limb designed by Hugh Herr—to its wearer's brain activity. A similar study, one featuring a different interface, has used an operator's brainwaves to drive a motorized wheelchair with high accuracy [43]. Dramatized BCI technology is an ever popular trope in science fiction, but, apart from the researchers who work to develop it, few understand how far the scientific community has come in making the fantasy a reality. As research continues to unlock the meaning contained within the electrical activity of the human brain, engineers will be able to design BCI systems of increased sophistication and efficacy.

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APPENDIX

The following code was modified from the original BCI module designed by Dr. Ou Bai. Its purpose is to run offline testing with only the beta band using the same functions and platforms as the original online tests:

```
function btv_ProstheticSwitch_Beta_cali_vr_OFFLINE(varargin)

%% Brain-Computer Interface to Virtual reality (BCI2VR)
%% Offline version of btv_ProstheticSwitch_Beta_cali_vr: a reconfiguration of
%%Ou Bai's program intended for offline data use. Calculates the accuracy of
%%EEG data given in epochs of 750 samples, corresponding with the amplifier's
%%sampling rate of 250 Hz in steps with a 3 second duration.
%% Ver. 1.0.0 04-02-11 Copyright by Ou Bai-Modification by Chris Hagerty-Hoff
%%

global btv;

if nargin == 0,
 %% Initialze Parameters for Virtual Environment

btv.vr.settings.SubjectName = 'Subject';
 %% Subject Name

btv.vr.settings.numberOfRepeats = 30;
 %% Number of Repeats between active motor imagery and relax

btv.vr.settings.eegChanIndex = 1:7;
 %% List all EEG channels that will be used

btv.vr.settings.betaDecimate = 3;
 %% Decimate rate for beta filtering

btv.vr.settings.betaFilterLeng = 64;
 %% Filter length for the beta bandpass filter

btv.vr.settings.barRange = [0 2];
```

```
 %% Bar axis range

btv.vr.OfflineLength = 750 ;
 %% The number of samples to be processed per offline epoch.

btv.vr.settings.samplesCorrection = 10;
 %% The average value across channels and freqeuncy band, the data will
 %% be rejected, i.e. no detection will be made.

btv.vr.settings.falsePositiveTolerant    =   0.05;
  %% The expected false positive rate

elseif ischar(varargin{1})
  %% INVOKE NAMED SUBFUNCTION OR CALLBACK
    try
        eval([ 'feval(' varargin{:} ');']);
    catch ErrCode
        errordlg(ErrCode.message, ['BCI2VR: ' mfilename]);
        vr_stop;
    end
end
return %% END MAIN
```

The following code decimates the raw data and filters it across the beta band using the filter shown in *Figure 9* before averaging the output across all seven signals:

```
function feature=featureExtract(sig)

global btv;

bLeng=length(decimate(sig(:,1),btv.vr.settings.betaDecimate));

bxx=zeros(bLeng,size(sig,2));

for i=1:size(sig,2)
    bxx(:,i)=decimate(sig(:,i),btv.vr.settings.betaDecimate);
end

bxx=filter(btv.vr.ersdsw.buf.bbBeta,1,bxx);

bfx=mean(abs(bxx(btv.vr.settings.betaFilterLeng+1:end,:)));

feature=mean(bfx);
 %% Average across channels for beta activity


return
```

Feature extraction is handled by the following code:

```
function flag=detectIntention

global btv;
%% Feature extraction

fSamples=mean(btv.vr.ersdsw.buf.ersPow(btv.vr.ersdsw.buf.trialSaved-
btv.vr.settings.detectMovAvg+1:btv.vr.ersdsw.buf.trialSaved,:,:)...
    -btv.vr.ersdsw.buf.erdPow(btv.vr.ersdsw.buf.trialSaved-
btv.vr.settings.detectMovAvg+1:btv.vr.ersdsw.buf.trialSaved,:,:),1);

cSamples=zeros(1,750);
 %%Creates an empty array for data transcription of epochs with 750 samples

for i=750
      cSamples(1,i)=fSamples(1,btv.vr.ersdsw.buf.fIndex(i,1),
      btv.vr.ersdsw.buf.fIndex(i,2));
end

[a,b,c]=mldpredict(2,cSamples,btv.vr.ersdsw.buf.detectModel);

dMLDist=c.gx(:,1)-c.gx(:,2);

if dMLDist>=btv.vr.ersdsw.buf.detectThreshold
    flag=1;
else
    flag=2;
end
```

Next, classification is done in the same manner as the original program:

```
%% Create classification model

if btv.vr.ersdsw.buf.currentNumberRepeat >= 20,

samples=[btv.vr.ersdsw.buf.samplesActive(1:btv.vr.ersdsw.buf.currentNumberRep
eat,:);btv.vr.ersdsw.buf.samplesRelax(1:btv.vr.ersdsw.buf.currentNumberRepeat
,:)];

targets=[ones(btv.vr.ersdsw.buf.currentNumberRepeat,1);2*ones(btv.vr.ersdsw.b
uf.currentNumberRepeat,1)];

    mldModel=mldtrain(targets,samples);

    [plabels,accuracy]=mldpredict(targets,samples,mldModel);

    aa=find(plabels(btv.vr.ersdsw.buf.currentNumberRepeat+1:end,1)==1);

    fPosRate=length(aa)/(length(plabels==1));

    mldModel.accuracy=accuracy;

    mldModel.plabels=plabels;

    mldModel.fPosRate=fPosRate;

    mldModel.std=sqrt(pinv(mldModel.pinvCov));
```