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The effects of mental training on brain computer interface performance with distractions

John LaRocco

THE EFFECTS OF MENTAL TRAINING ON BRAIN COMPUTER INTERFACE PERFORMANCE WITH DISTRACTIONS

by
John LaRocco

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ABSTRACT

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2008/11

Robi Polikar, Ph.D.
Master of Science in Electrical and Computer Engineering

The overall success of a brain computer interface (BCI) is largely dependent on the features used to make decisions. Noise in the electroencephalography (EEG) increases the difficulty of acquiring meaningful features. Previous literature suggests teaching subjects meditation and relaxation techniques may improve features relevant to BCI operation. The purpose of this study was to investigate performance on several cognitive protocols for both individuals who use meditation techniques and those who do not use these techniques. Both groups were given a motor imagery based BCI protocol, a P300 speller BCI, a verbal learning task, and an N-back test. No significant difference in performance was found between meditation and control groups. Our research does suggest however, significant differences for the P300 and motor imagery protocols may be found if a larger group (>20 subjects per class) is recruited.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 STUDY INTRODUCTION

A brain computer interface (BCI) system is a relatively new piece of technology in which a subject's brain signals are converted to control signals for an external device with the potential to assist the physically impaired [**1**]. Many unfortunate individuals have little or no control over their bodies due to neurodegenerative disorders (e. g. "Lou Gehrig's Disease," otherwise known as amyotrophic lateral sclerosis). Motor neuron diseases cause gradual loss and impairment of motor control; such impairment ranges from the ability to move limbs and extremities to being unable to breathe without mechanical assistance. Some patients retain a fully functional intellect, but they have little or no ability to communicate with the outside world. These patients are effectively "locked in," as prisoners inside their own bodies [**1**].

A BCI allows a patient to interact with the outside world, through the means of a prosthetic device. BCI systems rely on the integration of biosignal processing and feedback to train both subject and device to achieve communication and interaction with the outside world through the device [**2**]. BCI devices use many types of signals from the brain. The most common signal used in BCI is electroencephalography (EEG). Alternatives (e. g. MRI) are often cost-prohibitive, so EEG machines with surface electrodes are more common in BCI applications [**1**].

For an EEG-based BCI system, signal processing and pattern recognition tasks are the primary computational tasks. EEG is a non-stationary signal, meaning the spectral content of EEG changes over time [**2**]. EEG is also noisy, making processing and analyzing it a challenging task.

Common features derived from within EEG are evoked and used to control a device. BCI systems employ sequences of stimuli referred to in the context of the experiment as protocols [**1**].

Two of the most frequently used EEG-based BCI control systems are motor imagery and event-related potential (ERP) based protocols [**2**]. Motor imagery entails a subject encoding certain motor skills as different control signals for a device [**3**]. ERPs are specific types of EEG signals triggered via certain sensory inputs. An example of an ERP commonly used for BCI purposes is the P300 [**4**]. The P300 is a positive EEG spike that appears approximately 300 milliseconds after the start of a stimulus (e. g. a flashing light).

The P300 is often used in a P300 speller protocol, which allows a subject to spell words by selecting individual letters [**4**]. EEG signal processing, BCI systems, common features in EEG, and the algorithms associated with each are discussed in greater detail in Section 2.

Both motor imagery and P300 speller based protocols may benefit from a particular type of mental training [**2**], [**5**], and [**6**]. Meditation is a category of mental exercises that allows for greater control of one's physiological responses. While often used as a spiritual or relaxation technique, meditation does generate notable changes in the mind and body of an individual [**7**]. Some physiological changes occur outside of the state. Notable changes in practitioners include a drop in heart rate, reduction of oxygen consumed, and less physical tension. Although meditation may reduce stress, the mental benefits were of interest to BCI-related research [**8**]. Previous studies have examined the effects of mental training upon one type of BCI protocol at a time. A comprehensive study of meditation and BCI should include several different types of protocols. The purpose of the study was to examine the effects of meditation on BCI performance on subjects at different levels of distraction.

Meditation may play an important role in BCI performance because overlap exists in the certain EEG frequency bands that are utilized. The lower frequency bands (<8 Hz) and alpha band (8-12

Hz) are reported change in those subjects that perform frequent meditation. Many BCI protocols utilize features based on the alpha (8-12 Hz) and beta (13-30 Hz) bands [**9**]. If subjects who have received meditation training have significantly different levels of spectral power in EEG bands, then these subjects are potentially able to achieve finer control of BCI systems. If concentration and focus are improved, then errors due to subject distractions could be reduced. If meditation techniques provide a significant change in BCI performance, then instruction of meditation techniques may prove a useful improvement to BCI subject training. Additional information on meditation is provided in Section 2.2.

1.2 STUDY OBJECTIVES

The purpose of the study was to compare the performance of meditation practitioners and non-practitioners for different mental tasks. For BCI protocols, the performances of each group with and without distraction were compared. A significant difference in performance may indicate meditation does potentially assist in BCI applications. If a subject with knowledge of meditation more efficiently controls a BCI device, then training time can be reduced and BCI performance may improve.

A subject's BCI performance may depend on that individual's concentration and focus on the task being performed. The chance of distraction is significantly greater outside of a controlled laboratory or clinical setting. If a subject is distracted, then the subject's performance on the BCI may drop. Meditation is used as a way to tune out distractions. The effect of meditation on BCI performance, with and without distractions, was investigated. The protocols used to test the hypothesis are described in Chapter 3.

1.3 CONTRIBUTIONS OF STUDY

The purpose of the study was to determine whether a group of meditation practitioners could perform significantly better than non-practitioners, on BCI protocols and memory tests. No significant differences were measured, between the meditation and control groups; however, the meditation group performed consistently better in most tests. We believe, the inconclusive results are due to the small sample size that was available for the study. This study was the first to investigate the effects of meditation on a P300 speller protocol.

1.4 ORGANIZATION OF THESIS

The thesis is organized into the following sections. Chapter 1 provides basic background information on the motivation for the work. Chapter 2 provides a detailed literature review regarding BCI, EEG, meditation, and relevant statistical analysis techniques. All relevant aspects of data acquisition, preprocessing, feature extraction, and pattern recognition are also described in Chapter 2. Chapter 3 describes the individual protocols and testing schedule. Chapter 4 presents the results. Chapter 5 discusses the significance of the results, conclusions, possible sources of error, and suggestions for future work.

CHAPTER 2: BACKGROUND

2.1 BRAIN COMPUTER INTERFACE

2.1.1 DEFINITION

A BCI system is a pathway between the brain and a secondary device [**1**]. Signals from the brain are used as control signals for the external device. An invasive BCI involves acquiring signals from directly inside the brain. In a non-invasive BCI, signals are acquired without direct connection with the brain. If a subject receives feedback from a BCI system, it is a closed loop BCI.

Electroencephalography (EEG) is commonly used for BCI. EEG-based BCIs comprise the majority of BCI control signals due to their low cost and non-invasive nature compared with alternatives [**2**]. However, EEG is a noisy, non-stationary signal. It is sensitive to eye blinks, muscle movements, and other noise. Therefore, many BCI systems attempt to use signal-processing techniques to improve the signal. Other BCI systems use biofeedback and subject confirmation to determine control. All systems rely on a combination of subject training and machine learning [**2**]. Signal processing techniques relevant to the BCI protocols employed in the study are discussed in greater detail in Section 2.1.5.

Invasive BCIs using electrocorticography (ECoG) have a number of distinct advantages and disadvantages when compared to surface EEG. Invasive BCIs have a much clearer signal than non-invasive BCIs [**1**] [**2**]. Without the skull between the brain and electrodes, the device is able to read signals with significantly less interference. Such an implant is normally permanent or

long term. A number of drawbacks are innate with an invasive BCI system [**1**]. A major drawback is the disruptive effect on surrounding tissues. The device is inserted into brain tissue, which may cause a number of related problems.

The materials used in an invasive implant must be biocompatible [**1**]. Substances must not be toxic, or elicit an unexpected or unwanted response from the surrounding tissue. Metallic implants corrode and release particulate matter; polymers degrade over time; ceramics may be brittle; and composite materials share the flaws of their components [**1**]. In addition to biocompatibility and toxicity concerns, the presence of the implant is possibly disruptive to the neural tissue [**1**]. When an implant consisting of sharp metal electrodes is inserted into sensitive neural tissue, the implant disrupts more than cells. One of the electrodes may penetrate a blood vessel, causing bleeding inside the brain. Inflammation around the area of the implant is also possible. Scar tissue also forms around the site. Such factors degrade the implant and decrease the performance of the system itself [**1**]. Due to the difficulty of inserting an invasive implant and potential complications, which can arise, non-invasive BCI systems are often preferred over invasive BCI systems [**1**].

Regardless of semiotics and definitions, all BCI devices and systems have common elements [**2**], as Figure 2.1 shows. A signal is first acquired. Then, signal processing techniques are applied to remove unwanted elements of the signal. Feature extraction is performed on the signal. The features are then used to train a classifier. The classifier is then used to determine what sort of feedback to provide for each input [**3**].

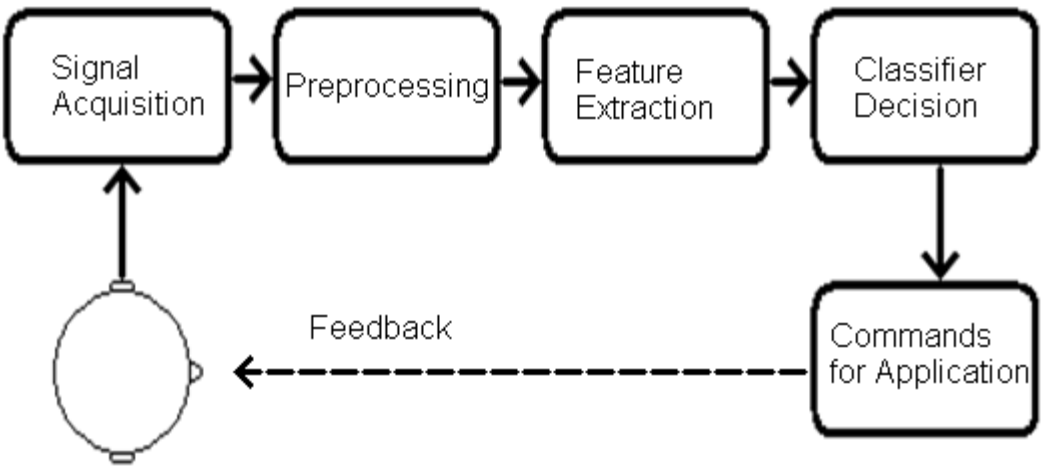


Figure 2.1: Brain Computer Interface Concept Diagram

The particular series of instructions, steps, and stimuli that makes up an experiment is called a protocol. In the context of BCI research, a protocol includes specific stimuli to attempt to evoke specific neural features. Each BCI system includes common steps. The common elements are signal processing, feature extraction, and a classifier [**2**]. Many BCI systems offer feedback to the subject. Others do not; for these systems, the primary processing is done offline. As shown in the BCI system diagram, signal acquisition is only the first phase. After acquisition, the next step is preprocessing. In the preprocessing phase: the signal is amplified, artifacts are rejected, the signal is filtered, baseline correction is performed, segments of time are sorted into epochs, and the signal is prepared for feature extraction [**10**]. After feature extraction, a classifier makes a decision based on the features. The classifier decision leans to commands for the application, which may or may not provide feedback to the subject. The BCI system diagram in Figure 2.1 is independent of the type of signal used. EEG is a common type of signal used for BCI [**2**], and it was used in the study.

2.1.2 ELECTROENCEPHALOGRAPHY

Electroencephalography is the recording of electrical activity, as obtained from surface electrodes on the scalp. The first EEG experiments were performed in the late nineteenth century and early twentieth century; by the 1950s, the technology was commonplace [**1**]. It was used primarily in hospitals and in medical research. The primary medical uses were to detect signs of mental activity in catatonic patients, distinguish epileptic seizures, locate regions of the brain affected by seizures, as well as many related applications. EEG is used to monitor other procedures, such as examining the depths of anesthesia or mental activity during surgery. EEG is also used to monitor for non-convulsive seizures and the mental activities of comatose patients. EEG is commonly used in cognitive psychology, neuroscience, and cognitive science research [**1**].

2.1.3 SIGNAL ACQUISITION

2.1.3.1 ELECTRODE PLACEMENT

The first step of EEG recording is placement of electrodes to acquire the electrical activity within the skull. While the electrical potential in an individual neuron is hard to measure from outside the body, the electrical fields the neurons generate can be measured by surface scalp electrodes as in encephalography (EEG). The most common method of electrode placement is known as the 10-20 system [**11**]. Figure 2.2 [**12**] demonstrates the placement of the main electrodes on the head.

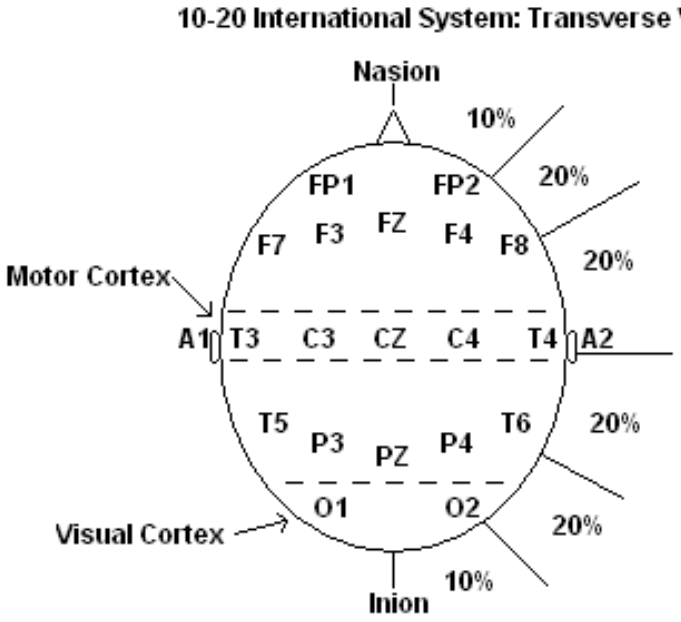


Figure 2.2: International 10-20 System from Sagittal (A) and Transverse (B)

The skull and skin make reading electric activities in the brain difficult with surface electrodes. Due to ease of setup and low cost, surface electrodes are the most common way to measure electrical activity in the brain [**12**]. The resulting activity is faint; it is often measured in microvolts. EEG requires amplification before any preprocessing is applied.

2.1.3.2 SPECTRAL BANDS

EEG is a non-stationary signal, meaning its spectral content changes over time. Individual frequencies within EEG are typically grouped into different frequency bands. The bands are the delta band (1-4 Hz), theta band (4-7 Hz), alpha band (8-12 Hz), beta band (13-30 Hz), and gamma band (>30 Hz) [**1**]. Looking at specific bands and their power spectra allows researchers to focus on more relevant neural activity. Isolating activity to a specific frequency band reduces the possibility of artifacts and noise interfering with desired data [**1**]. Some frequency bands are of greater interest to different areas of research.

Of particular relevance to BCI researchers is the mu band. The mu band (7-14 Hz) has a similar frequency range as the alpha band (8-12 Hz). The mu band is most commonly witnessed in the motor cortex, which is the region of the brain that controls voluntary motor actions. The electrodes CZ, C3, and C4 correspond most directly to the location of the motor cortex in the 10-20 System. The mu band signals appear in the motor cortex when physical action is being considered [**1**], and actually undertaken. The cause of the occurrence is due to specialized cells known as mirror neurons. More information on a protocol utilizing spectral content and features is described in greater detail in Section 3.

2.1.3.3 EVENT-RELATED POTENTIALS

The event-related potential (ERP) is a relevant aspect of EEG. ERPs are brain responses evoked by conscious thought, in response to a variety of stimulus [**13**]. Certain types of ERPs appear regardless of the type of stimulus, such as visual, auditory, tactile, or other. The variety of stimuli that evoke ERPs means that even otherwise impaired subjects may be able to evoke them. For example, a visually impaired person may use an auditory stimulus instead of a visual one.

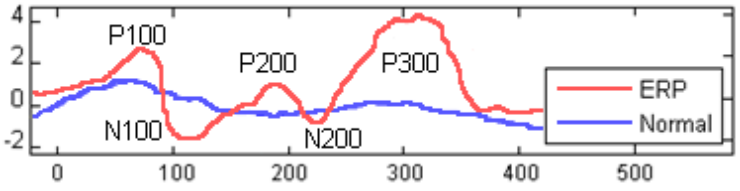


Figure 2.3: Sample ERP

ERPs are commonly named by a simple convention: while acronyms are sometimes used, it is common to use either the letter P or N (for either positive or negative polarity with respect to the ground) followed by the number of milliseconds after the stimulus. For example, the P300 is a positive peak appearing approximately 300 ms after the stimulus, as shown in Figure 2.3. It is

proceeded in the example by other ERPs: the P100, a positive peak at approximately 100 ms after the stimulus; the N100, a negative ERP following the P100; the P200, a positive peak at approximately 200 ms; an N200, a negative ERP after the P200; and the P300, a positive peak at approximately 300 ms. While several types of responses can be evoked reliably, an ERP may be difficult to discern from other, ongoing brain processes. A stimulus is repeated several times; each occurrence is called an epoch or trial, and time locked responses are averaged to obtain ERPs.

ERPs are commonly used in medicine and research. In medicine, they are used to detect potential neurological disorders [**13**]. In research, ERPs have been used to detect sensory responses in different parts of the brain. In particular, the P300 has been used in a very common type of BCI protocol. The P300 speller is a BCI protocol that allows a subject to select different characters and options on the basis of counting observations of visual or auditory stimulus. More information on the P300 speller protocol can be found in Section 3.

2.1.3.4 NOISE

A problem with amplifying signals is that any source of noise or interference is amplified as well. Certain physical actions may interfere with EEG recordings. Eye movements (e. g. blinking) cause low-frequency artifacts, as shown in Figure 2.4.

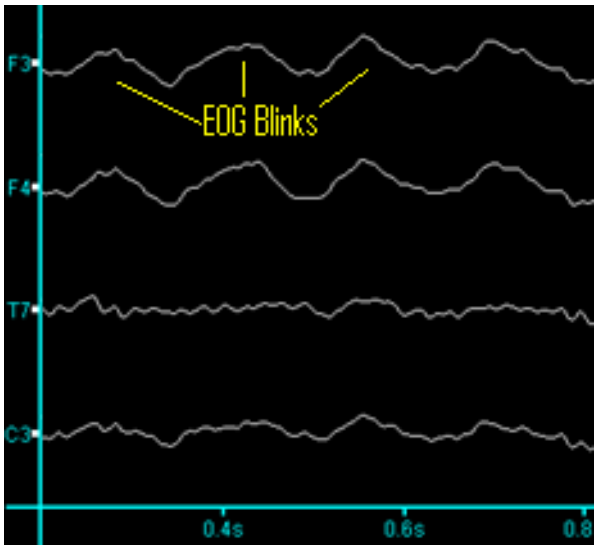


Figure 2.4: Filtered EOG (Electrooculography) Artifacts in EEG

In Figure 2.4, the two channels at the top, (F3 and F4), have larger amplitude peaks than other channels in the figure. The scale of the particular image is not magnified, so the artifacts seem to have less relative difference compared to their surroundings. Each of the large peaks corresponds to a subject blinking. The electrooculogram (EOG) blinking and eye motion artifacts primarily affect the readings on the frontal electrodes F3 and F4. As shown in Figure 2.1, the two electrodes are placed close to the subject's forehead and eyes. The EOG artifact amplitudes are largest near the eyes. If an electrode is placed further away from the eyes, the EEG is less susceptible towards EOG artifacts. There are methods to reduce the contributions of EOG artifacts. One such method is spatial filtering, which is described in Section 2.1.4 in greater detail.

Muscular action can also cause artifacts. The movement of jaw muscles creates high-frequency electromyographic (EMG) noise [**10**], as shown in Figure 2.5.

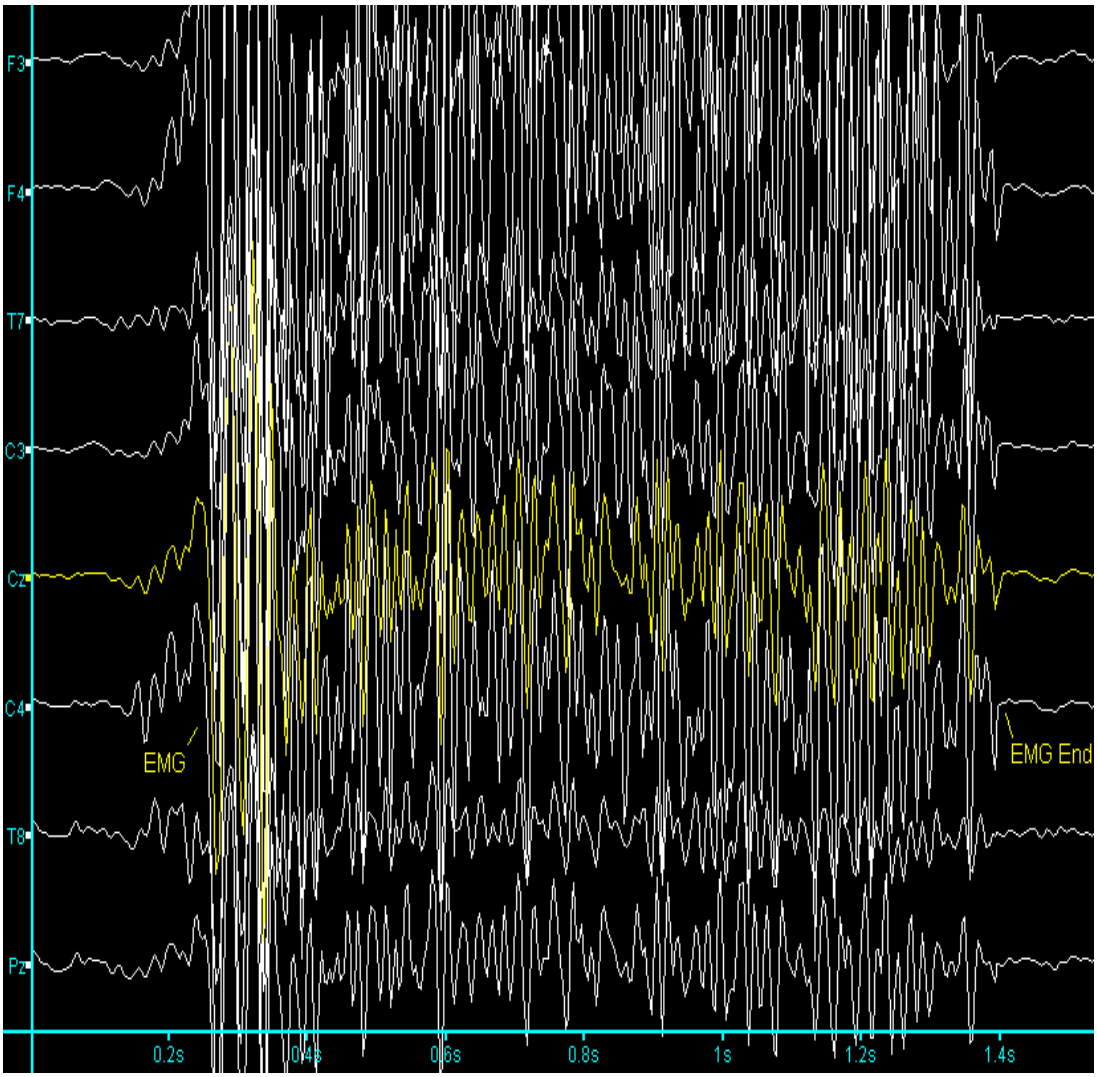


Figure 2.5: High Frequency EMG Noise in EEG

Unlike the ocular artifacts, the EMG artifacts have higher frequencies (>20 Hz). EMG may also affect all electrodes and channels across the head. A low pass filter is able to minimize the contributions from EMG artifacts in EEG.

Other sources of biological noise may also exist in EEG (e. g. the electrocardiogram [ECG].) ECG is the electrical signal from the heart. ECG ranges from .5-100 Hz [**1**]. An ambient source of noise is the 60 Hz electrical noise from overhead wires. A notch filter, which removes only a very narrow band of frequency, removes such noise.

Other ambient noise sources are reduced through properly shielded and insulated cables. A common method to reduce different types of noise is a bandpass filter. The bandpass filter is used to remove both low-frequency and high-frequency noise, and is thus a versatile type of filter for use with EEG. Filtering, and other signal processing techniques, are essential to successful EEG recording.

2.1.4 SIGNAL PROCESSING TECHNIQUES

2.1.4.1 PREPROCESSING TECHNIQUES

Signals are any phenomenon measurable over time and quantifiable on a sensor. The measurement at a particular point in time is the amplitude. A one dimensional analog signal is a continuous signal with a continuous amplitude [**14**]. Many biological signals are analog signals, because they are continuous. If time is measured in discrete units, a signal is discrete. Analog signals are converted to digital signals by sampling and quantization. According to the Nyquist sampling theorem, a signal must be sampled at least twice the highest frequency present in the signal [**14**]

EEG is a primarily low-frequency (<100 Hz) analog signal, so sampling requirements are not as high as higher-frequency signals [**1**]. Since the frequencies of note in EEG in the study are lower than 30 Hz, a sampling rate of 250 samples per second was used. Bandpass filtering allows the advantages of both highpass and lowpass filtering. A lower order bandpass filter between .5 Hz and 30 Hz was used. Considerable overlap exists between signal processing and feature extraction techniques. As such, information regarding feature extraction techniques relevant to the study are detailed in Section 2.1.5.

2.1.5 FEATURE EXTRACTION

In feature extraction, signals are processed with various transforms or filtering. Examples of common features in EEG are spectral features (e. g. autoregressive coefficients) [**2**], and temporal features (e. g. P300 peak). Feature extraction methods can be combined with each other, or different sets of features taken from each subject. Autoregressive coefficients were used in the study, which are described in more detail in the next section.

2.1.5.1 SPECTRAL POWER

Each frequency component contributes to the amplitude signal. The Discrete Fourier Transform (DFT) is a commonly used way to switch between the temporal and frequency domains. The frequency domain term, $X(k)$, is found by summing the product of time domain signal $x(n)$ and a complex exponential for each sample *n* of total samples *N*, as shown in (2.1).

$$X(k) = \sum_{n=0}^{N-1} x(n) * e^{-j2\pi kn/N} \qquad 0 \leq k \leq N-1 \tag{2.1}$$

Using DFT $X(k)$ of time domain signal $x(n)$, the components of a signal can be analyzed in the frequency domain [**14**], as shown in (2.2).

$$P_x(k) = \frac{|X(k)|^2}{(2\pi)} \tag{2.2}$$

The power spectral density (PSD) shows how each frequency component contributes to signal amplitude. Other methods can be used to estimate spectral density when the signal is non-stationary. A simple method of estimation, shown in (2.3), is the periodogram, which is used for a finite length signal. In (2.3), f_s is the sampling rate and $N$is the power of 2 greater than signal length *L*, or length of the DFT.

$$P_x(k) = \frac{|X(k)|^2}{(f_s * N)} \quad (2.3)$$

A problem with the periodogram method is that the signal is truncated, introducing Gibbs' effect and side lobes. The side lobes cause distortion and are known as spectral leaks. Spectral leaks cause a lack of resolution, or ability to discern between spectral components. A method of generating an estimate with less variance is Welch's method [**15**]. Welch's method consists of calculating several periodograms from different time segments of a signal and averaging them together. The resulting estimate has less variance, but it also has distorted resolution. Estimation of the PSD is a common transformation in BCI protocols. However, autoregressive methods are frequently used instead of periodograms [**2**].

Autoregressive estimation methods, such as the Burg algorithm, allow for an estimate of PSD while avoiding spectral leakage and increased resolution with shorter data lengths [**16**]. The spectral estimates of EEG are commonly used features used in brain computer interface [**2**]. More in-depth discussion of the Burg algorithm can be found in Section 2.1.5.2.

2.1.5.2 AUTOREGRESSIVE COEFFICIENTS

Autoregressive coefficients estimating the power spectral density (PSD) of EEG have been used in a number of BCI systems. AR features from the alpha and beta bands have been used in the cases of several motor-imagery protocols [**3**], [**9**], and [**1**]. Autoregressive coefficients are the result of fitting a polynomial to either a segment of EEG data or the power spectrum of such a segment. The use of a time-varying error function with autoregressive coefficients is known as adaptive autoregression (AAR). A related algorithm is ARMA, or autoregressive moving average. ARMA combines autoregressive filters with the moving average model of time series [**17**]. For the study, sliding window AR estimates of the PSD calculated using the Burg method

were used as features. The number of autoregressive coefficients is equivalent to model order *M*, and take the form shown in (2.4). The coefficients **a**(*m*) estimate the power spectrum of EEG signal *x(n).*

$$\mathbf{a}(m) = [a_{M,}\ldots,a_1],\ m = 1, 2, \ldots, M \tag{2.4}$$

The autoregressive model assumes that signal *x(n)* is the sum of a deterministic sequence and white noise process *v(n)*, as in (2.5).

$$x(n) = \sum_{m=1}^{M} a(m)x(n-m) + v(n) \tag{2.5}$$

The Burg algorithm does not directly compute autoregressive coefficients $\mathbf{a}(m)$; instead it estimates reflection coefficients $\mathbf{k}(m)$. The Burg algorithm is known as a lattice predictor because it appears as a lattice when written as a block diagram for a filter [**17**]. The Burg method starts with cost function (2.6) [**18**].

$$J_{fb,m} = \frac{1}{2}E[|f_m(n)|^2 + |b_m(n)|^2],\ m = 1, 2, \ldots, M \tag{2.6}$$

The cost function contains the terms forward prediction error $f_m(n)$ and backward prediction error $b_m(n)$ [**19**].

$$f_m(n) = f_{m-1}(n) + k_m{}^* b_{m-1}(n-1) \tag{2.7}$$

$$b_m(n) = b_{m-1}(n-1) + k_m f_{m-1}(n) \tag{2.8}$$

Error terms $f_m(n)$ and $b_m(n)$ are computed using prior terms $f_{m-1}(n)$ and $b_{m-1}(n-1)$. Reflection coefficients k_m and complex conjugate $k_m{}^*$ act to update the error terms between iterations [**20**], and can be substituted under some circumstances. Substituting functions (2.7) and (2.8) into (2.6) yields equation (2.9).

$$J_{fb,m} = \frac{1}{2}(E[|f_{m-1}(n)|^2] + E[|b_{m-1}(n-1)|^2])(1 + |k_m|^2) + k_m E[|f_{m-1}(n) {b_{m-1}}^*(n-1)|^2]$$

$$+ {k_m}^* E[|b_{m-1}(n-1) + f_{m-1}(n)|^2] \quad (2.9)$$

Cost function (2.9) is then differentiated with respect to k_m, and set equal to zero. By ensuring the condition (2.10) is met, $J_{fb,m}$ is minimized.

$$\frac{\partial J_{fb,m}}{\partial k_m} = 0 \quad (2.10)$$

Equation (2.9) can be rewritten in the form in (2.11). The optimal value of k_m, k_{opt}, is computed.

$$k_{opt} = -\frac{2E[b_{m-1}(n-1){f_{m-1}}^*(n)]}{E[|f_{m-1}(n)|^2 + |b_{m-1}(n-1)|^2]} \quad (2.11)$$

EEG is a non-stationary signal, but it may be assumed to be stationary under certain circumstances to simplify calculations. EEG can therefore be assumed to be ergodic, or have similar states repeat over time [**1**]. Equation (2.11) becomes (2.12).

$$k_{opt} = -\frac{2\sum_{i=1}^{n}[b_{m-1}(i-1){f_{m-1}}^*(i)]}{\sum_{i=1}^{n}[|f_{m-1}(i)|^2 + |b_{m-1}(i-1)|^2]} \quad (2.12)$$

The estimate of k_{opt} depends on the data input $x(n)$ [**17**]. For each value of *m*, vector $\mathbf{k}(m)$, is formed from each value of k_{opt}, and shown in (2.13).

$$\mathbf{k}(m) = [k_{M,}\ldots,k_1],\ m = 1, 2, \ldots., M \quad (2.13)$$

With $\mathbf{k}(m)$ calculated, the optimal forward and backward projections may be computed for each entry in the vector, using (2.7) and (2.8) for each *m*. The projected values are used to compute the *M* by *M* matrix of autoregressive coefficient estimates, **A**. The first sample of input signal $x(n)$, $x(0)$, is set equal to $f_m(0)$ and $b_m(0)$ to initialize computation.

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,M} \\ \vdots & \ddots & \vdots \\ a_{M,1} & \cdots & a_{M,M} \end{bmatrix} \tag{2.14}$$

Coefficients within **A** are computed using (2.15). Variable i is a sequence of numbers referring to matrix indices [**21**].

$$a_{m,m} = \begin{cases} a_{m-1,i} + k_m * a_{m-1,m-i}, & i = 1,2,\ldots,m-1 \\ k_m, & i = m \end{cases} \tag{2.15}$$

The first row of $\boldsymbol{A}$ is taken, and it becomes vector $\mathbf{a}(m)$. This procedure is known as the direct method [**22**]. Vector $\mathbf{a}(m)$ becomes the feature set extracted from *x(n).*

In the implementation of autoregressive spectral analysis used by BCI2000 software, the order of the filter determines which coefficient will correspond to which spectral band. With a passband of .5 to 30 Hz and filter order of 16, each AR coefficient corresponds to a band of 1.85 Hz [**10**]. The Burg algorithm is used in the motor imagery BCI protocol [**10**]. An example of the Burg method of AR estimation is provided below. The example is a signal comprising the sum of three sinusoids: one at 8 Hz, one at 16 Hz, and one at 24 Hz. Zero mean white noise with a standard deviation of 4 is also added to the signal. The sampling rate is 1000 samples per second. The signal is in Figure 2.6, and the spectrum (using a 42nd order model) is shown in Figure 2.7.

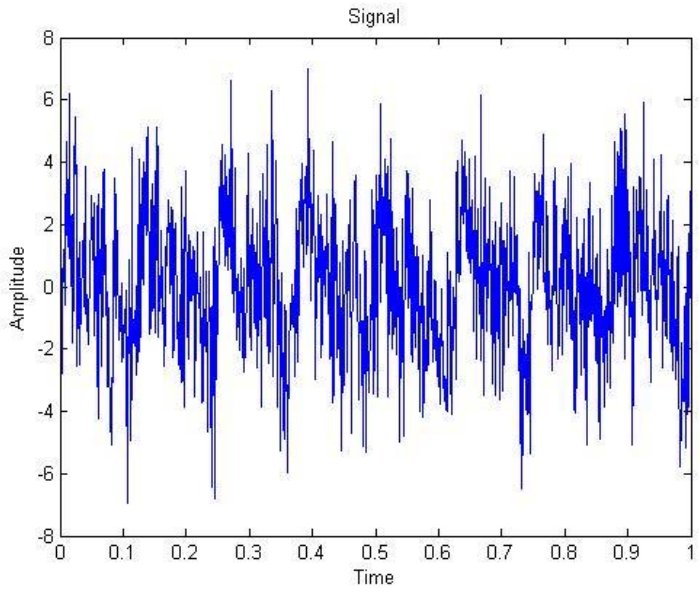


Figure 2.6: Sinusoidal Signal

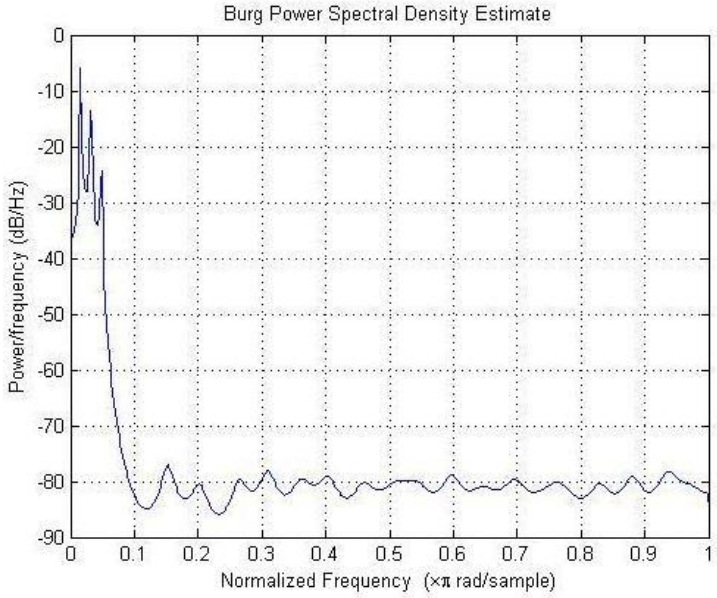


Figure 2.7: Burg Spectrum Estimation

Another method of estimating the PSD is the periodogram, which is computed using (2.3) [**15**]. A periodogram of the same sinusoidal signal was computed and shown in Figure 2.8.

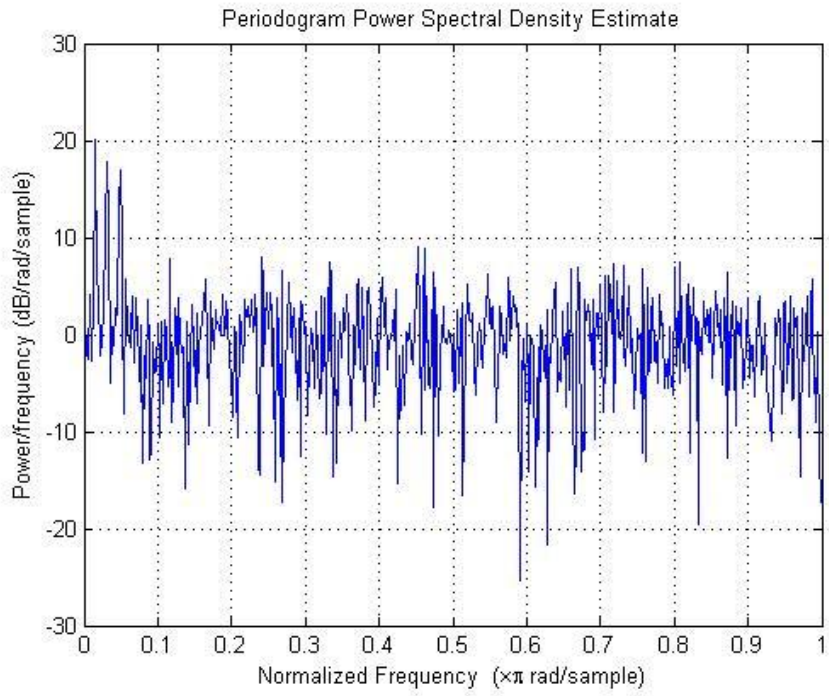


Figure 2.8: Periodogram PSD Estimate

Welch's method, as discussed earlier, was also used to take an estimate. Welch's method produces a "cleaner" estimate than the periodogram, with less prominent variance. The averaging procedure acts as a form of filtering in Welch's method [**15**]. Averaging the estimates together reduces variance, but at the cost of resolution. Compared to the periodogram and Welch's method, the Burg algorithm has less variance when calculating close frequencies at low levels of noise [**17**].

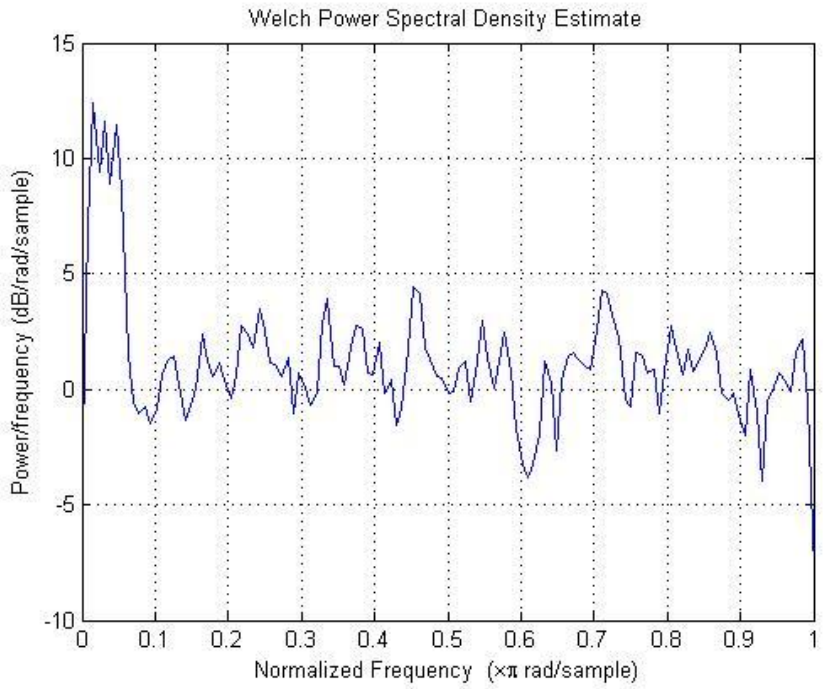


Figure 2.9: Welch PSD Estimate

Beyond estimating the PSD, another common method of feature extraction is spatial filtering.

2.1.5.3 SPATIAL FILTERING

Even with a sufficiently high sampling frequency and bandpass filter, EEG still suffers from additional problems. One problem is poor spatial resolution. Spatial resolution refers to the ability to discern the specific spatial origin of a source signal. Methods exist to reconstruct intracranial sources [**1**], although reconstruction is often computationally laborious. Spatial filtering refers to minimizing likely sources of noise by applying of a set of coefficients that reducing the contributions of the noise inputs. Spatial filtering techniques, including common spatial patterns and Laplacian filters, are used for signal processing and feature extraction [**1**].

Two types of spatial filters were employed in the study, each for a separate protocol. The first spatial filter, $\mathbf{W_1}$**,** was employed in the motor imagery protocol to reduce the contributions of

noise and artifacts. A weighted matrix $\mathbf{W}_1$ is formed and multiplied with the signal. Matrix **X**, holding *M* samples per *N* channels, represents an unfiltered signal. Matrix $\mathbf{X_f}$ represents a spatially filtered matrix of identical dimensions. The dimensions of $\mathbf{W}_1$ must allow for matrix multiplication with **X** such that (2.16) holds true.

$$\mathbf{X_f}=\mathbf{W}_1*\mathbf{X} \tag{2.16}$$

The terms are calculated using a procedure equivalent to common average reference (CAR), where for each channel outputs of *N* nearby electrodes are added and averaged together in $\mathbf{X_{av}}$ in (2.17) before being subtracted as a baseline from the recorded values $\mathbf{X_{chan}}$, forming $\mathbf{X_{CAR}}$ in (2.18) [**10**].

$$\mathbf{X_{av}} = \frac{(\sum_{i=1}^{N} \mathbf{X_i})}{N} \tag{2.17}$$

$$\mathbf{X_{CAR}} = \mathbf{X_{chan}} - \mathbf{X_{av}} \tag{2.18}$$

Spatial filter $\mathbf{W_1}$ performs the same task utilizing matrix coefficients based on spatial location of nearest electrodes. As in CAR, the spatial filter subtracts a fraction of nearby electrode inputs. The three most important channels in the motor imagery protocol are the channels on the motor cortex: C3, CZ, and C4 [**1**]. A major source of noise is EOG. Three new channels are set up: C3_Out ($\mathbf{C3_{OUT}}$), CZ_Out ($\mathbf{CZ_{OUT}}$), and C4_Out ($\mathbf{C4_{OUT}}$). Each channel consists of a combination of a primary electrode (C3, CZ, or C4), subtracting the contributions of its neighbors not directly on the motor cortex. Each electrode has a numerical vector containing recorded values. Electrode C3 (represented as vector **C3**) has four neighbors, represented by the following vectors: **F3**, **T3**, **CZ**, and **PZ**. Electrode CZ (represented as **CZ**) has five neighbors, represented by the following vectors: **F3**, **F4**, **C3**, **C4**, and **PZ**. Electrode C4 (represented as **C4**)

has four neighbors, represented by the following vectors: **F4**, **T4**, **CZ**, and **PZ**. If an electrode is a neighbor to electrodes C3, CZ, or C4, function (2.19) is used to calculate coefficient *c*. Variable *k* is the total number of neighboring electrodes. For electrode CZ, the value of *k* is 5. For electrodes C3 and C4, the value of *k* is 4.

$$c = -\frac{\mathbf{1}}{k} \tag{2.19}$$

The dimensions of the matrix are 3 x 8.

	F3	F4	T3	C3	CZ	C4	T4	PZ
C3_OUT	-.25	0	-.25	1	-.25	0	0	-.25
CZ_OUT	-.2	-.2	0	-.2	1	-.2	0	-.2
C4_OUT	0	-.25	0	0	-.25	1	-.25	-.25

Figure 2.10: Spatial Filter Coefficients

The matrix was computed using the procedure below.

Table 2.1: *Matrix Coefficient Calculation Procedure*

Coefficient Calculation
1) Select Electrode: C3, CZ, or C4 2) Set *k* to number of neighbors of electrode 3) Compare electrode to list: F3, F4, T3, T4, TZ, PZ, C3, C4, CZ A) If electrode is neighbor to selected one, compute coefficient with (2.19) B) If electrode is not a neighbor to selected one, set coefficient to 0 C) If electrode is the same as selected one, set coefficient to 1

The formulae used to calculate output channels $\mathbf{C3_{OUT}}$, $\mathbf{CZ_{OUT}}$, and $\mathbf{C4_{OUT}}$ are shown in (2.20), (2.21), and (2.22).

$$\mathbf{C3_{OUT}} = \mathbf{C3} - .25 * (\mathbf{CZ} + \mathbf{PZ} + \mathbf{F3} + \mathbf{T3}) \quad (2.20)$$

$$\mathbf{CZ_{OUT}} = \mathbf{CZ} - .2 * (\mathbf{F3} + \mathbf{F4} + \mathbf{C3} + \mathbf{C4} + \mathbf{PZ}) \quad (2.21)$$

$$\mathbf{C4_{OUT}} = \mathbf{C4} - .25 * (\mathbf{F4} + \mathbf{T4} + \mathbf{CZ} + \mathbf{PZ}) \quad (2.22)$$

Another form of spatial filtering is Fisher linear discriminant [**23**]. FLD is a form of spatial projection that separates two groups by covariance. Fisher linear discriminant weight matrix **w**, was applied both to motor imagery and P300 speller protocols to set a threshold between subsets of data. More information about FLD can be found in Section 2.1.5.5. In addition to spatial filtering, a key step in the process of finding an appropriate threshold is averaging across time.

2.1.5.4 TEMPORAL AVERAGING

Temporal averaging is a procedure that combines several trials of EEG data into a single averaged trial. A trial is repeated on each participant a number of times, and EEG from each trial is recorded. Each recorded trial is referred to as an "epoch" of data. The resulting averaged epoch represents a combination of its components. Benefits of temporal averaging include increasing computational efficiency, removal of noise, and assistance with thresholding. Temporal averaging of epochs may serve as a rudimentary form of filtering, removing noise with each average. The level of noise may decrease when more epochs are averaged together. A threshold may be set up; the threshold must be high enough such that noise is unlikely to cross it. Temporal averaging can assist in setting a threshold.

Thresholding uses the raw amplitude value to determine whether or not an instance reaches the threshold. A threshold is required to be sufficiently high so that random noise does not cross it [**1**].

First, several separate trials are necessary. Assume matrix **X** contains *N* epochs with *M* samples each. The epochs are averaged together into a single vector $\mathbf{X_{av}}$ of *M* samples.

$$\mathbf{X_{av}} = \frac{\left(\sum_{i=1}^{N} \mathbf{X_i}\right)}{N} \tag{2.23}$$

Three sample noisy signals (each a 1-Hz sinusoid with increasing levels of noise) are shown below in Figure 2.11. Each signal is recorded for 1 second; each represents a separate epoch of data from the same electrode. As the noise in the image increases, discerning the signal becomes difficult.

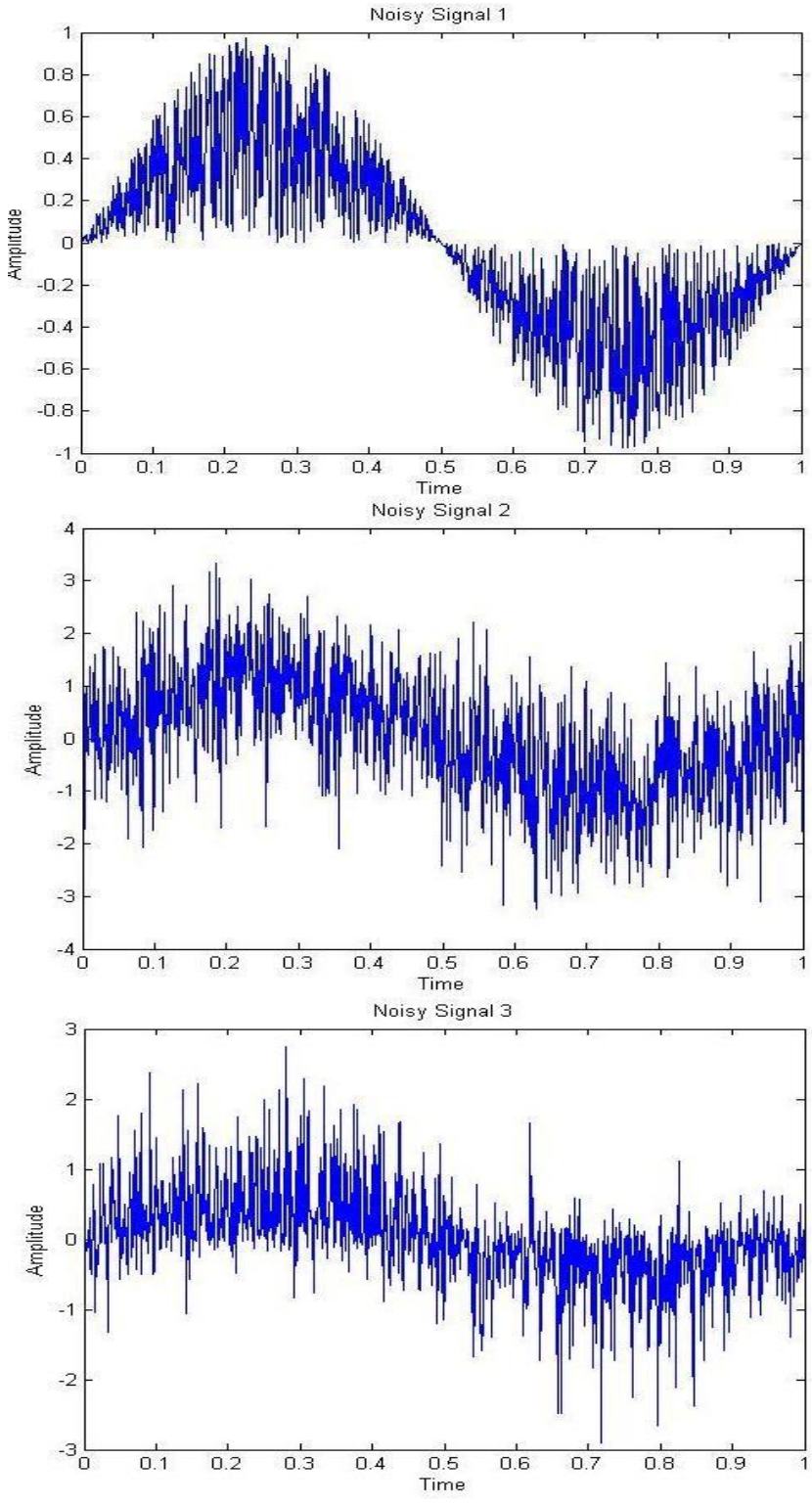


Figure 2.11: 1-Hz Sinusoid with Increasing Noise

Once the noisy signal is averaged with other three epochs, the noise is reduced. During analysis, individual epochs are averaged together for each electrode. Figure 2.12 shows the example epochs averaged together.

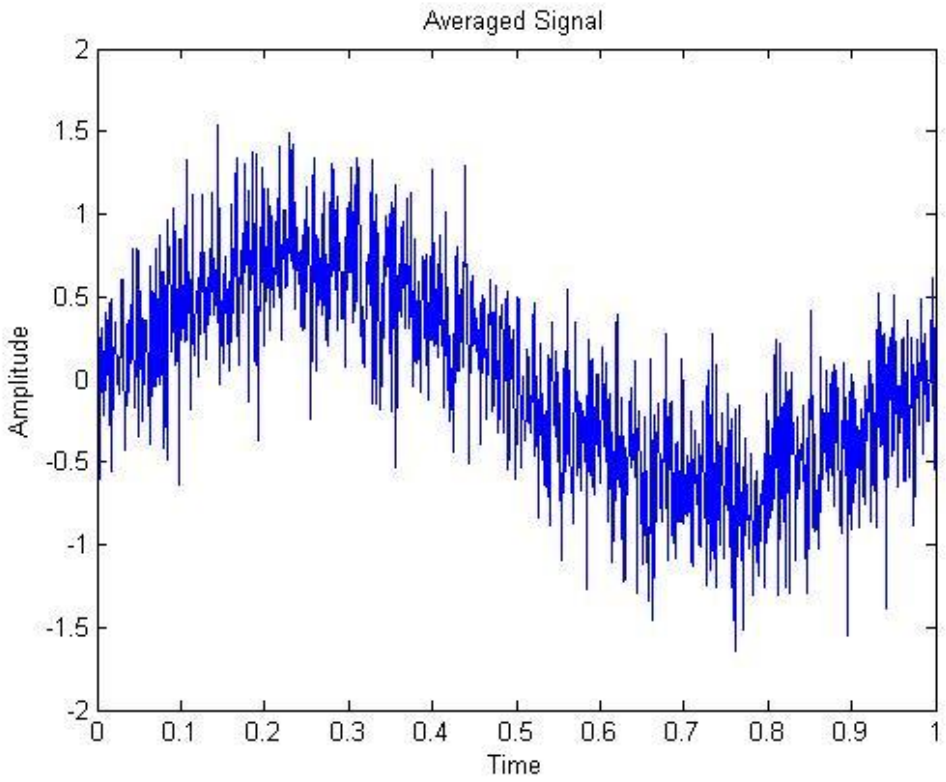


Figure 2.12: Averaged Signal

Collecting more epochs takes more time. A larger number of epochs can more effectively remove noise. The tradeoff between time spent and collecting epochs is an issue in protocol design. Temporal averaging can be used in preprocessing, by subtracting the mean of the signal from the pre-stimulus segment. Averaging epochs together may act as a form of feature extraction. Averaging is useful for extracting a temporal feature, such as a P300 spike. The feature is often located by averaging several trials together [**13**], as performed in the previous example.

Averaging trials can assist in setting a threshold for use in machine learning. A specific algorithm is able to greatly assist with setting thresholds, Fisher linear discriminant [**23**].

2.1.5.5 FISHER LINEAR DISCRIMINANT

Fisher linear discriminant (FLD) is a form of feature extraction closely related to linear discriminant analysis (LDA). Both originate in the theory of Bayesian decision making, which is based on associating class labels with data points based on probabilities. FLD and LDA are a form of supervised learning, where the class label is known [**24**]. A discriminant function is a function that maximizes the distances between two or more classes [**24**]. A linear discriminant is a linear combination of input matrix **X**. Input matrix **X** contains *n* vectors **x** of features *d* dimensions long.

$$g(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + w_0 \tag{2.24}$$

Vector **w** is a component of the larger weight matrix $\mathbf{W_2}$,, which projects the input units along a decision boundary. Constant $w_0$represents the threshold weight or bias, and it is equal to zero if a line passes through the origin [**24**]. The weight matrix **w** projects a dataset along a single line. First, **w** must be computed if optimal threshold is to be set between two datasets, D_1 and D_2, each representing a class. Vector $\mathbf{m}_\mathrm{i}$ is the *d*-dimensional sample mean of class *i* given by (2.25).

$$\mathbf{m}_\mathrm{i} = \frac{\mathbf{1}}{\boldsymbol{n_i}} \sum_{\mathbf{x}\in\mathbf{D_i}} \mathbf{x} \tag{2.25}$$

Sample means $\mathbf{m}_1$ and $\mathbf{m}_2$ may be projected to a new coordinate system, as shown in (2.26).

$$\mathbf{m}_\mathbf{i}' = \frac{\mathbf{1}}{\boldsymbol{n_i}} \sum_{\mathbf{x}\in\mathbf{D_i}} \mathbf{w}^{\mathrm{T}}\mathbf{m_i} \tag{2.26}$$

Distance between projections of the sample means can be computed by combining (2.25) and (2.26) into (2.27).

$$|\mathbf{m}_1' - \mathbf{m}_2'| = |\mathbf{w}^{\mathrm{T}}(\mathbf{m}_1 - \mathbf{m}_2)| \tag{2.27}$$

Instead of calculating the variances of each data subset, scatter matrices for the original projected data are calculated for each data subset within **x**. The scatter matrix of **x** can be defined as (2.28).

$$\mathbf{S_i} = \sum_{\mathbf{x}\in\mathbf{D_i}}(\mathbf{x} - \mathbf{m_i})(\mathbf{x} - \mathbf{m_i})^{\mathbf{T}} \tag{2.28}$$

In the case of two subsets, a combined term can be computed. The term is the within class scatter matrix $\mathbf{S_W}$ for datasets D_1 and D_2.

$$\mathbf{S_W} = \mathbf{S_1} + \mathbf{S_2} \tag{2.29}$$

The square of each scatter matrix for projected data and the separations of both projected scatter matrices can be written as (2.30), which can be obtained by combining and squaring equations (2.27), (2.28), and (2.29) [**24**].

$$(\mathbf{m}_1' - \mathbf{m}_2')^2 = \mathbf{w}^{\mathbf{T}}(\mathbf{m}_1 - \mathbf{m}_2)(\mathbf{m}_1 - \mathbf{m}_2)^{\mathrm{T}}\mathbf{w} = \mathbf{w}^{\mathrm{T}}\mathbf{S_B}\mathbf{w} \tag{2.30}$$

The between-class scatter matrix is computed in (2.31).

$$\mathbf{S_B} = (\mathbf{m_1} - \mathbf{m_2})(\mathbf{m_1} - \mathbf{m_2})^{\mathrm{T}} \tag{2.31}$$

A new quantity, *J(***w***)* is written in terms of the scatter matrices.

$$J(\mathbf{w}) = \frac{\mathbf{w}^{\mathbf{T}}\mathbf{S_B}\mathbf{w}}{\mathbf{w}^{\mathbf{T}}\mathbf{S_W}\mathbf{w}} \tag{2.32}$$

The quantity $J(\mathbf{w})$, a generalized Rayleigh quotient [**24**], is maximized at the optimal weight matrix where (2.24) is equal to zero. The relationship that maximizes (2.37) must satisfy (2.38) for some constant λ.

$$\mathbf{S_B w} = \lambda \mathbf{S_W w} \tag{2.33}$$

From (2.33), constant λ can be solved for eigenvalues. Since $\mathbf{S_B w}$ points in the direction of $(\mathbf{m_1} - \mathbf{m_2})$, solving an eigenvalue problem is not necessary to solve for weight vector **w** [**24**].

$$\mathbf{w} = \mathbf{S_W^{-1}}(\mathbf{m_1} - \mathbf{m_2}) \tag{2.34}$$

The weight vector **w** allows the projection of data with the maximum ratio of between-class scatter to within-class scatter for each vector **x**. The problem has been simplified from *d* dimensions to one. Even if $w_0$is not ideal, FLD is often robust enough to produce a close estimate. The weights for each subject are used to calibrate and train the BCI2000 software. After data has been projected using **w**, the problem becomes pattern recognition. Combined with averaging, Fisher linear discriminant is used to set electrode weights for the P300 speller protocol.

2.1.6 PATTERN RECOGNITION

After feature extraction, a classification algorithm is typically employed. For BCI applications, one of the most common types of classifier is linear discriminant analysis (LDA). LDA computes a linear boundary between two classes. Linear Discriminant Analysis [**25**], is among the simplest types of classifiers. LDA is partially based on Bayesian decision theory, which associates class labels with data points based on probability. LDA is considered a supervised learning technique, which means class labels are known. Due to its simplicity, LDA was used for the study.

2.1.6.1 LINEAR DISCRIMINANT ANALYSIS

A Linear Discriminant Analysis (LDA) classifier was used in this study. A linear discriminant is a linear combination of component vector **x**. As stated before, LDA sets up a decision boundary between categories.

$$g(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + w_0 \tag{2.35}$$

The coefficients of **x** correspond to input units. Vector **w** is the weight matrix, which projects the input **x** along a decision boundary. After the weight vector **w** is calculated as shown in Section 2.1.5.5, a threshold is set. Constant $w_0$represents the threshold weights or bias [**24**]. When $g(\mathbf{x})$ is linear, the decision boundary is a hyperplane [**24**]. If two vectors, $\mathbf{x_1}$ and $\mathbf{x_2}$, are on the decision boundary, both discriminants are equivalent, shown as in (2.36).

$$\mathbf{w}^{\mathrm{T}}\mathbf{x_1} + w_0 = \mathbf{w}^{\mathrm{T}}\mathbf{x_2} + w_0 \tag{2.36}$$

Equation (2.36) can also be written as in (2.37). In (2.37), distance between the vectors becomes zero.

$$\mathbf{w}^{\mathrm{T}}(\mathbf{x_1} - \mathbf{x_2}) = 0 \tag{2.37}$$

The weight vector **w** is thus perpendicular to vectors lying on the hyperplane *H*. Hyperplane *H* divides an area into separate regions. An optimal decision boundary is where (2.35) is equal to zero.

In the case of a two class problem, two separate spaces, $\mathbf{R_1}$ and $\mathbf{R_2}$, are separated by the hyperplane. If point x_i exists where $g(x_i) > 0$, then the point is in $\mathbf{R_1}$. If point x_i exists where $g(x_i) < 0$, then it is in $\mathbf{R_2}$. The function $g(\mathbf{x})$ gives the distance from point x_i to the hyperplane *H*. The distance from normally projected x_p to point x_i is *r*.

$$g(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + w_0 = r||\mathbf{w}|| \tag{2.38}$$

The location of every point with respect to hyperplane *H* determines the region, and thus, the category classification. LDA was used as the classification algorithm for both the motor imagery protocol and P300 speller protocol for its simplicity.

A Gaussian toy dataset, shown below, demonstrates LDA. Two groups, Group 1 (symbolized by red "x" shapes) and Group 2 (symbolized by blue circles), are separated by an LDA classifier. Hyperplane *H* is denoted by the purple line. LDA is a robust, computationally efficient algorithm, and it is sufficient for real-time classification in BCI protocols [**2**]. Figure 2.13 shows an example of two non-overlapping Gaussian datasets separated by the decision boundary.

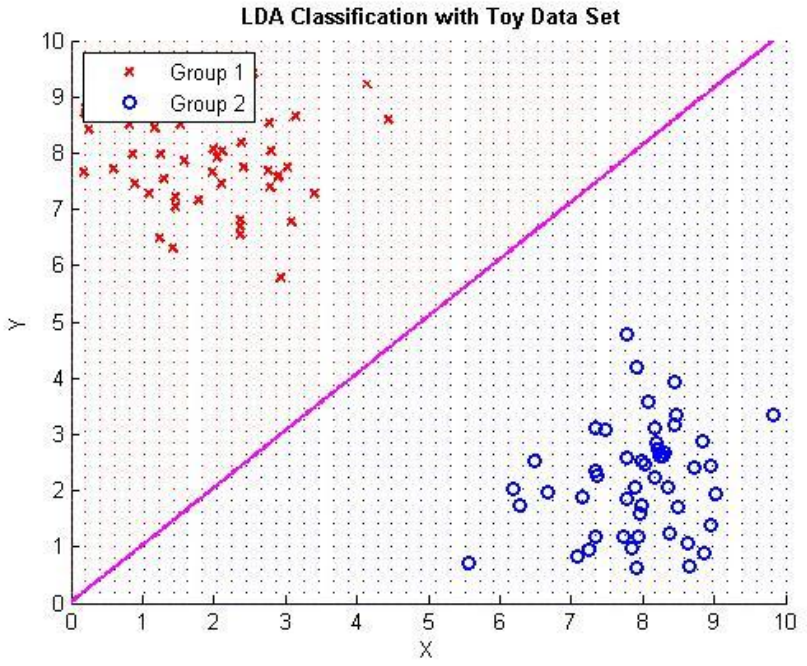


Figure 2.13: LDA Classifier Visual Example

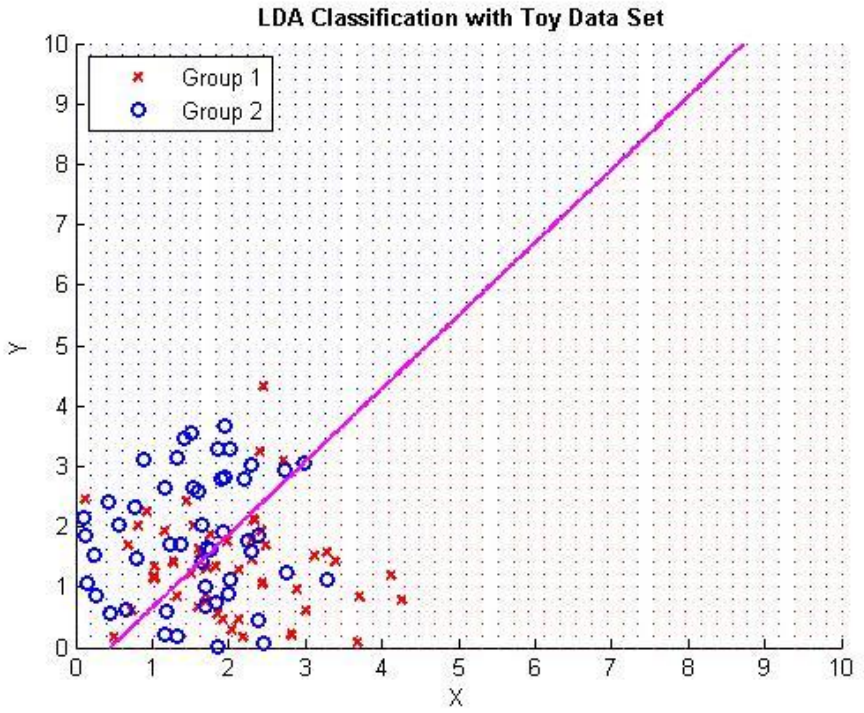


Figure 2.14: LDA with Overlapping Gaussian Datasets

Figure 2.14 demonstrates two Gaussian datasets with a greater degree of overlap, to demonstrate a situation that LDA does not perform optimally. Some overlap occurs between the categories in Figure 2.14 because the classifier is a simple linear model. Misclassifications can and do occur with overlapping and more realistic datasets, such as the two datasets in Figure 2.14. LDA is able to operate in near real-time, allowing for rapid feedback in both of the BCI protocols in the study. BCI protocols are discussed in greater detail in Section 3.

2.2 MEDITATION

2.2.1 OVERVIEW

Meditation is a general name for a broad spectrum of mental training and relaxation techniques. For purposes of simplicity, the terms *meditation* and *mental training* are used interchangeably in

this thesis. It has been used by individuals from as diverse backgrounds as religious and spiritual figures to physical trainers. Meditation has its roots in religious traditions. It has been used in Buddhism, Hinduism, and other religions for thousands of years. In recent times, many of the techniques have been introduced to scientific study [**7**]. Many of the techniques were also incorporated into generalized relaxation techniques, such as progressive muscle relaxation. While relaxation techniques can function as mental training, the goal becomes to get an individual to relax, rather than any form of religious exercise [**26**].

2.2.2 COMMON TYPES

The definition of "meditation" covers a number of distinct styles. For purposes of the study, a system of organized instruction into physical relaxation, biofeedback control, and focus training are defined as meditation. The list of techniques includes, but is not limited to the following: Yoga, Zen meditation, progressive muscle relaxation, transcendental meditation, tai-chi, and certain "soft" martial arts (such as aikido and wushu) [**7**]. Many broad and commonly overlapping categories of techniques exist. Mantra-based techniques (e. g. transcendental meditation) allow meditation through the recitation of "mantras" or phrases. Physical relaxation techniques (e. g. progressive muscle relaxation, tai-chi, and yoga) include calisthenics and breath control. Concentration-based techniques (e. g. Zen) focus on breath control and mental training [**7**].

The wide range of techniques makes consistency across subjects difficult. Ideally, all subjects would possess a similar background; however, finding a large enough sample of volunteers and participants is difficult for similar meditation backgrounds and skills, leading to a compromise between experimental consistency and available population size. Meditation styles, such as transcendental meditation and Zen meditation, are clear candidates being for included in the

meditation group. Certain martial arts that include meditation techniques in their training are also included. Mediation-like martial styles include wushu and aikido. The meditation techniques can cause similar neurological and physiological changes [**7**].

2.2.3 PHYSICAL CHANGES

The relevant forms of mental training have common traits. One common trait is neuroplasticity. For years, neuroscientists believed that connections between neurons were permanent once established, and neuronal connections lasted into adulthood. Neuroplasticity is the opposite idea; its premise is that even adults can change existing connections and make new connections between neurons [**27**]. Meditation and mental training allows even adults to have increased "neuroplasticity" [**7**]. Other neurological changes may be present in EEG [**5**].

Meditation-induced changes are present in EEG. In an individual who meditates frequently, specific frequency bands often appear at a higher spectral power [**8**]. A related feature is that of alpha blocking. Alpha blocking is the suppression and decrease in the spectral power of the alpha band when the subject is exposed to an auditory stimulus. When a stimulus is repeated for an untrained person, EEG shows alpha blocking only after the first exposure to the stimulus. As it is repeated, a subject is able to tone it out. In a meditative state, alpha blocking occurs whenever the auditory stimulus is repeated. In the meditative state, the meditation practitioner becomes more aware of his or her body. Meditation practitioners do not instinctively "tune out" ambient sounds, and thus become more aware of their own environments during in a state of meditation, and outside it [**7**]. In addition, evidence exists that P300 latency is decreased and P300 amplitudes increased with frequent meditation [**28**].

Other physiological changes may occur outside of the brain. Meditation allows a subject to consciously control biofeedback. While it may vary with the individual, common experiences occur in longtime practitioners. Due to the highly subjective nature of meditation experiences, it is difficult to quantify their effects [**7**].

However, some tests have been performed on participants who are experienced with mental training and meditation. Noticeable results have been induced by meditation practices, such as in [**8**], [**29**], and [**5**]. Meditation and biofeedback allow a person to increase control over his or her own body in ways he or she had not previously imagined. Decreased stress, tension, and blood pressure as well as better control of breathing, focus, and concentration are some of the more common benefits [**30**] [**31**] [**32**].

Many of the changes are often correlated. A subject is able to concentrate and focus longer; therefore, the subject is able to become increasingly aware of tension in his or her body [**7**]. Gradually, a person becomes increasingly aware of tension inside the body, and subconsciously is able to stay relaxed. The change in focus is applicable to the external world as well. With more control over internalized stress, the traditional causes of stress in the "externalized world" may not invoke the tension they once did [**31**]. The resistance to stress has been reported from meditation practitioners who face life or death situations on a daily basis, and people who seek to cope with the stresses of everyday life [**7**]. However, meditation training time can vary greatly.

In meditation instruction, the amount of time to sufficiently train a subject is highly variable. In this study, subjects with experience in meditation were preferred, and the bare minimum to be eligible for the meditation group was assumed to be 1 month [**7**]; however, most subjects should surpass the minimum in training time. Ideally, subjects should have at least experience

measurable in months of practicing meditation. Due to variety in individual proficiency, a meditator may not have proficiency directly relating towards his or her length of experience [**7**]. Statistical tests were conducted based on the performances of the meditation and control groups in the following section.

2.3 STATISTICAL ANALYSIS

2.3.1 OVERVIEW

The primary method of statistical analysis used in the study is analysis of variance (ANOVA). ANOVA is mathematically similar to a t-test, except ANOVA is used when the study design contains several comparison groups. ANOVA compares group means by analyzing comparisons of variance estimates. If sample means are taken from a population, two possibilities exist as to why differences are present. One possibility is that they are members in different groups. The other possibility is difference due to chance. ANOVA is based on the fact that two independent estimates of the population variance are obtained from the sample. Ratios are formed for each estimate. One ratio of estimates is sensitive to error. The other ratio of estimates is sensitive to the between groups estimate and within groups estimate.

In conducting ANOVA, there are three main assumptions: (a) each measurement is independent, (b) the cases are normally distributed, and (c) variances are equal in groups [**30**]. ANOVA is known for being robust, even if populations do not conform to the assumptions, especially regarding the third assumption. The robustness makes ANOVA suitable for investigating the significances of groups of unknown variance.

2.3.2 ONE WAY ANOVA

The simplest case of ANOVA is a single factor (one way) comparison with two or more populations. Variable *I* is the total number of treatments or populations. Variable μ_1 is the mean of the first population or treatment, or first sample mean. Variable μ_2 is the mean of the second treatment or population, or second sample mean. If more than two cases exist, other sample means up to μ_I are represented. Assume there is a Case 1 (H_0), where all means are equal. Case 1 is described shown in (2.39).

$$\text{Case 1 } (H_0): \quad \mu_1 = \mu_2 = \cdots = \mu_I \tag{2.39}$$

The alternative Case 2, in which the means are different, is (2.40).

$$\text{Case 2 } (H_a): \quad \mu_1 \neq \mu_I \tag{2.40}$$

H_0, or Case 1, refers to the null hypothesis, or what must be disproven statistically. The alternative, Case 2 or H_a, is the alternative hypothesis. The goal is to determine whether enough statistical evidence exists to accept the alternative and reject the null hypothesis. H_0 is tested, so that ANOVA tests if all means represent the same population mean [**30**].

The primary goal of ANOVA is to calculate a statistic called f_{obs}, which simultaneously allows all levels to be compared. The comparison shows whether any of the means (such as $\mu_1$or μ_2) are different. Datasets may contain smaller portions, known as levels, corresponding to the absence or intensity of different factors or variables. The value of f_{obs} is calculated for all levels of a dataset in one-way ANOVA [**30**]. The calculated value of f_{obs} is compared with f_{crit}. The value of f_{crit} depends on the significance level and number of comparisons. If f_{obs} is not significant, there are no significant differences between the means.

A problem with ANOVA comparison is the exact location of a significant difference within a dataset is unknown. Post-hoc tests, each a single pair comparison, are then performed. The post-hoc tests are performed only when a significant difference is present [**31**].

ANOVA computes variance from two perspectives in the sample data, so both components in the population can be estimated. Instead of calling the terms *estimated variance*, they are called *mean square* terms. The two mean square groups are *mean square within groups* (MS_{wn}) and *mean square between groups* (MS_{bn}). MS_{wn} is an estimate of the variability within each population, and it describes the variability of individual scores in any of the samples. MS_{bn} shows the differences between levels of a factor, or how much the means of conditions differ from each other. The larger MS_{bn} is, the more it appears that null hypothesis H_0 is false. If H_0 is true in a comparison, then$MS_{bn}$is equal to MS_{wn}. A ratio of MS_{bn} and MS_{wn}, shown in (2.41) is used to calculate f_{obs}.

$$f_{obs} = \frac{MS_{bn}}{MS_{wn}} \tag{2.41}$$

Before MS_{bn} and MS_{wn} can be calculated, the estimated variance is necessary. To calculate the estimated variance, an operation called the "sum of the squared deviations" is performed. The term is shortened to the "sum of squares" [**30**]. The sum of each population $\sum X$ is computed, and also then the sum of squared terms is added to get squared sum $\sum X^2$. Other variables are the number of data points in a sample n, the total number of levels *k*, the sample mean $\bar{X}$, and total number of data points N. The terms $\sum X$, $\sum X^2$, $\bar{X}$, and n are found for each level. The terms $\sum X$, $\sum X^2$, and $\bar{X}$ are also found for the entire population. After the preliminary calculations, the sum of squares SS_{tot} for the entire population is found in (2.42).

$$SS_{tot} = \sum X_{tot}{}^2 - \frac{(\sum X_{tot})^2}{N} \tag{2.42}$$

The sum of squares for between groups is calculated next as shown in (2.43). The calculation of SS_{bn} is done for each level and subset of the entire cohort.

$$SS_{bn} = \sum(\frac{(\sum X_{level})^2}{n_{level}}) - \frac{(\sum X_{tot})^2}{N} \tag{2.43}$$

Computing the sum of squares within groups SS_{wn} is a matter of subtraction. Mathematically, SS_{tot} is equal to SS_{bn} plus SS_{wn}. SS_{wn} can be found by subtracting SS_{bn} from SS_{tot} in (2.44).

$$SS_{wn} = SS_{tot} - SS_{bn} \tag{2.44}$$

Calculating the degrees of freedom is the next step. The total degrees of freedom df_{tot}, degrees of freedom between groups df_{bn}, and degrees of freedom within groups df_{wn} are calculated as in (2.45), (2.46), and (2.47).

$$df_{tot} = N - 1 \tag{2.45}$$

$$df_{bn} = k - 1 \tag{2.46}$$

$$df_{wn} = N - k \tag{2.47}$$

The next step is to calculate mean squares MS_{bn} and MS_{wn}, as in (2.48) and (2.49).

$$MS_{bn} = \frac{SS_{bn}}{df_{bn}} \tag{2.48}$$

$$MS_{wn} = \frac{SS_{wn}}{df_{wn}} \tag{2.49}$$

With MS_{bn} and MS_{wn} obtained, f_{obs} can be calculated using (2.41). The values are displayed in an ANOVA table, as in Table 3.2.

Table 3.2: *Sample ANOVA Table*

Variance Source	Sum of Squares	df	Mean Square	F
Within-group	SS_{bn}	df_{bn}	MS_{bn}	f_{obs}
Between-group	SS_{wn}	df_{wn}	MS_{wn}	
Total	SS_{tot}	df_{tot}		

The sequence of steps includes calculating the sum of squares, calculating the degrees of freedom, calculating the mean squares, and obtaining f_{obs}. The value for f_{crit} is taken from a chart or table for f, such as in Figure 2.15 [**30**]. As shown in Figure 2.15, the f distribution is right-skewed.

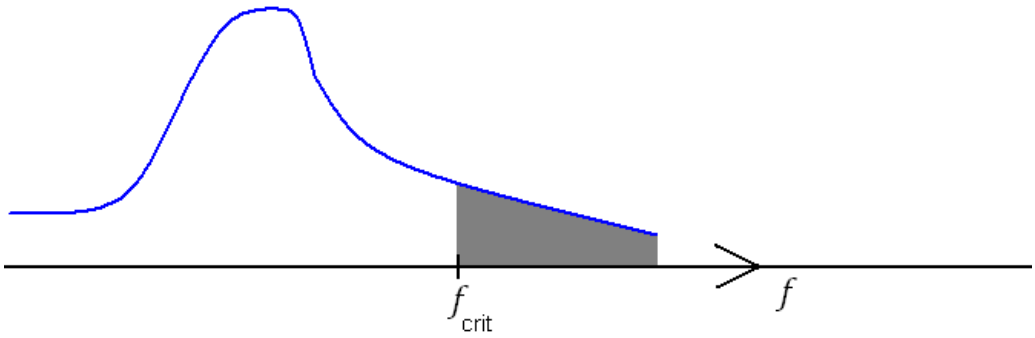


Figure 2.15: Distribution of *f* for 95% Confidence Interval

The *f* distribution is the sampling distribution showing the different *f* values when null hypothesis H_0 is true for all conditions in one population [**30**]. The *f* distribution is actually a family of curves, with the exact shape dependent on the degrees of freedom for each source of variance. If f_{obs} is greater than f_{crit}, it is considered highly unlikely that H_0 is true, so it is rejected. The principles of ANOVA can be applied to more complex cases.

2.3.3 MIXED MODEL ANOVA

The basic ANOVA computation can be adapted for different cases, such as mixed models with repeated measures. Mixed models ANOVA assumes multiple levels for within-subjects differences and between-subjects differences, as well as fixed and random effects. For the study, the primary distinction between-subjects is meditation or control. The within-subjects differences in the study are different levels of test protocols [**32**]. The multiple measurements for different levels for the within-subjects group are the "repeated measures" of the model.

The two types of relevant variables to mixed model ANOVA are fixed effects and random effects. Depending on the specific context, both fixed effects and random effects may either be between-subjects or within-subjects differences. A fixed effects model treats observed values as not random [**30**]. In the study, membership in the meditation or control groups is mutually exclusive for subjects. Random effects models treat observations as random, including different populations within. Mixed model ANOVA is robust regarding assumptions made whether an effect is fixed, random, or mixed. Both within-subjects and between-subjects levels may include both random effects and fixed effects [**31**].

As stated previously, assigning random and fixed effects is highly dependent on the specific ANOVA model used. In the study, the between subjects variables (e. g. group membership) and within subjects variables (e. g. scores for the different N-back tests) include both fixed and random effects [**31**]. The presence of both fixed and random effects with within-subjects and between-subjects variables makes the study a mixed model.

The mixed model is originally derived from a linear fixed effects model. The fitted data is assumed to be a linear combination of observed values and error. In matrix form, (2.50) is known

as the General Linear Model (GLM). GLM assumes that observed data is the result of a combination of fixed effects and random error.

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{E} \tag{2.50}$$

The term **y** is a vector representing *n* observed values. Vector **β** is filled with explanatory or dummy variables indicating group or level membership. Matrix **X** contains the linear regression parameters connecting fixed effects in **β** to observed values in **y**. Vector **E** represents random independent identically distributed (i. i. d.) error terms with a Gaussian distribution, mean of zero, and covariance matrix **R** [**33**]. The value of **R** can be computed for mixed models, as shown in (2.51).

$$\mathbf{R} = \sigma^2 \mathbf{I_n} \tag{2.51}$$

Variable σ is the standard deviation of the population. Identity matrix $\mathbf{I_n}$ is *n* by *n* dimensions, with *n* being the number of observations in **y**. The mixed model assumes that observed information is the result of fixed effects, random effects, and error. A term to represent random effects is inserted into GLM. GLM becomes a mixed model, as shown in (2.52).

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{Z\gamma} + \mathbf{E} \tag{2.52}$$

In (2.52), the matrix **Z** represents the linear regression parameters for matrix **γ**. Matrix **γ** contains explanatory or dummy variables corresponding to random effects, and has a covariance matrix **G** [**34**]. The covariance matrix of **y** in a mixed model, designated as **V,** can be assumed to be (2.53) due to assuming a normal distribution of random effects **γ** and error **E**.

$$\mathbf{V} = \mathbf{ZGZ^t} + \mathbf{R} \tag{2.53}$$

The exact values for $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are initially unknown; these values are estimated using the Henderson equations [**34**], shown in (2.54).

$$\begin{bmatrix} \mathbf{X^t R^{-1} X} & \mathbf{X^t R^{-1} Z} \\ \mathbf{Z^t R^{-1} X} & \mathbf{Z^t R^{-1} Z + G^{-1}} \end{bmatrix} \begin{bmatrix} \widehat{\boldsymbol{\beta}} \\ \hat{\boldsymbol{\gamma}} \end{bmatrix} = \begin{bmatrix} \mathbf{X^t\, R^{-1} y} \\ \mathbf{Z^t R^{-1} y} \end{bmatrix} \tag{2.54}$$

The estimated values are used to update the linearly regressive estimates $\mathbf{X}$ and $\mathbf{Z}$, and error $\boldsymbol{\epsilon}$. The computationally intensive estimation process is performed iteratively until an error goal is reached. The estimates for linear regressive matrices $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, $\widehat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}$, allow analysis to be performed for both fixed and random effects. Variables necessary for ANOVA (e. g. the sum of squares, mean sums, and values of f_{obs} for each level) can be computed after the estimation of the linear regressive matrices. SPSS software was used for the analysis. More information regarding the specifics of each protocol and specific ANOVA model used is described in Section 3.2.5.

CHAPTER 3: METHODS

3.1 PREVIOUS WORK

Researchers in several studies have investigated meditation and BCI performance [**5**], [**6**], and [**29**]. The largest of these studies [**6**], used nine subjects, three of whom were control, three of whom were instructed in meditation, and three of whom were given music lessons. The performance of the meditation subjects on a motor imagery BCI increased over the music and control groups. The previous experiments focused on small sample sizes and were largely constrained to motor-imagery BCI protocols. As of this study, no researcher has investigated a P300 BCI protocol comparing meditation and control groups.

Some literature [**28**] exists on the possibility of meditation subjects having noticeable changes to the P300. Therefore, the purpose of the study is to compare meditation and control groups, each with a larger sample size, and test for any significant differences in BCI performance. The results of previous studies comparing meditation and control groups suggested that even the subjects who have practiced meditation for even a short time may perform better on focus-related tests than the subjects who have not [**26**]. Relevant protocols include focus and memory tests to determine if the meditation group performs significantly different than the control group.

3.2 EXPERIMENTAL OVERVIEW

The study included 20 subjects, with 10 individuals in each group. Each subject was tasked with the same protocols. Two protocols were BCI protocols: the motor imagery protocol and P300

speller. Two were memory and focus tests: the verbal learning task and N-back test. Calibration was performed twice per subject: once for the motor imagery and once for the P300 speller. The subjects performed the motor imagery and P300 speller protocols under controlled conditions, and then performed both the motor imagery and P300 speller protocols under distraction. The distractions consisted of a set of headphones with a randomized selection of loud noises, distracting sounds, and voice recordings. The subject had to retain focus while performing the BCI task.

3.2.1 BCI SETUP AND CALIBRATION

A 40-channel Neuroscan NuAmps EEG amplifier with SCAN 4.4 software was used for signal acquisition. For BCI protocol feedback, BCI2000 software was used. Each subject underwent calibration for both motor imagery and the P300 speller. For each subject, 10 electrodes were used from the standard 10-20 system: F3, F4, T3, C3, CZ, C4, T4, T5, T6, and PZ. The electrodes T3, T4, C3, CZ, and C4 were selected for their proximity to the motor cortex. Two reference electrodes were used; the electrodes were placed on the mastoids behind the subject's ears. A ground electrode near the subject's forehead was also used. A notch filter at 60 Hz for overhead interference was used, along with a bandpass filter with a passband between .5 and 30 Hz.

Based on tutorials in the BCI 2000 software and other literature [**35**], eight of the non-reference electrodes were used at any given time for BCI protocols. For the motor imagery protocol, the electrodes F3, F4, T3, T4, C3, C4, CZ, and PZ were used. For the P300 spelling protocol, the electrodes F3, F4, T5, T6, C3, C4, CZ, and PZ were used. More information regarding the selection of the particular electrodes is described below. The motor imagery BCI and P300 speller protocols used a simple Linear Discriminant Analysis (LDA) classifier [**35**].

3.2.1.1 MOTOR IMAGERY SETUP AND CALIBRATION

A motor imagery BCI protocol often requires extensive subject training [**3**]. Thinking about performing physical activity has been shown to produce similar signals as an '*actual'* movement due to mirror neurons [**1**]. To calibrate the motor imagery experiment, a non-feedback protocol was used. Arrows pointing up, down, left, and right were shown sequentially on a monitor in random order. A one second rest period position was placed between each arrow image appearing and disappearing. Each stimulus was shown on the screen for two seconds. Each specific stimulus was meant to encode a particular motor imagery task. A left arrow directed the subject to imagine grasping with the left hand. A right arrow directed the subject to imagine grasping with the right hand. A down arrow directed the subject to imagine moving both feet. An up arrow directed the subject to imagine grasping with both hands. The time for the calibration protocol was 4 minutes in total [**10**]. The training epochs were temporally averaged (as explained in Section 2.1) together for each type of imagined motor action: left hand closed, right hand closed, both hands closed, or both feet lifted.

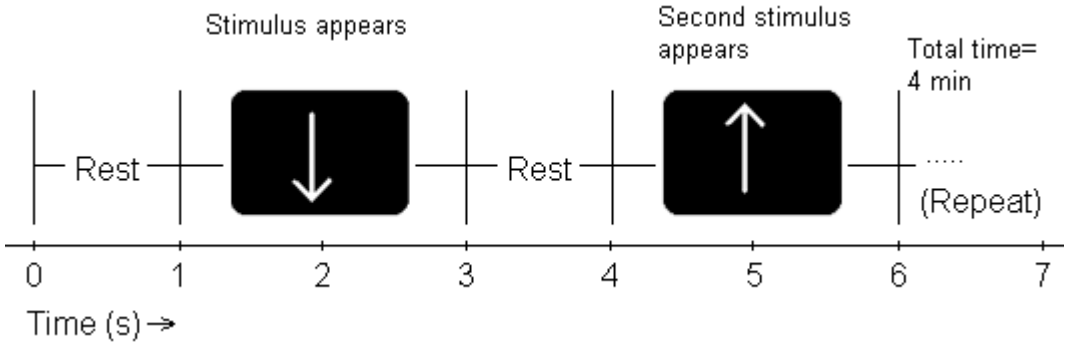


Figure 3.16: Mu Calibration Protocol Sequence

Afterwards, spectral features were computed from the calibration data, as shown in Section 2.1. A sixteenth order autoregressive model with a 500 ms sliding window was used for feature

extraction, based on quick calibration software instructions for untrained users [**10**]. Each coefficient represented a band of approximately 1.8 Hz between .5 Hz and 30 Hz. The most distinctive features for each subject were encoded into movements for a cursor. The subject thinking of one type of motor action was used to move a cursor upwards; thinking of a second motor action moved it downwards. The motor actions correlating to the most distinctive spectral values were used.

For the motor imagery protocol, the electrodes F3, F4, T3, T4, C3, C4, CZ, and PZ were used. The electrodes T3, T4, C3, CZ, and C4 were used due to their position on top of the motor cortex. PZ was used for its proximity to the motor cortex. F3 and F4 were utilized due to their proximity to the eyes and susceptibility towards blinking, and to further differentiate right and left brain activity [**10**].

Little distinctive differences were detected between the "move both hands" gesture and the "move only left/right hand" gesture. Thinking about lifting both feet and squeezing both hands commonly gave the most distinctive differences. The simplest correlation between gesture and cursor direction was to encode cursor movement "up" and "down" with thinking about squeezing both hands or lifting both legs. Squeezing with both hands was used to encode moving the cursor up, and lifting both legs was encoded to move the cursor down. When thinking about hand movement, EEG activity increased in the left and right sides of the motor cortex roughly around the locations of electrodes C3 and C4. When thinking about foot movement, EEG activity around the position of electrode CZ increased. Calibration was still essential to determine the specific frequency band of greatest difference.

The frequency bands with the highest spectral features allowed for a threshold-based LDA classifier to be set up, as shown in Section 2.1. The frequencies used in calibration were in the mu (7-14 Hz), alpha (8-12 Hz), and beta (13-30 Hz) bands [**9**] [**3**]. The electrodes that showed the greatest differences between the two classes were CZ, C3, and C4. A Laplacian filter, a 3 x 8 matrix $\mathbf{W_1}$, shown in Figure 2.10, amplified the contributions of CZ, C3, and C4, and minimized the contributions of F3 and F4 to reduce ocular artifacts.

The matrix was applied to all incoming data for the motor imagery protocol. Trials were averaged together for each subject, and a neural activity map was made, such as the example map shown in the center of Figure 3.17. The activity map denoted which region of the brain was most active for which task, and was instrumental in selecting which frequency band to use for each subject. A summary of the calibration process is shown in Figure 3.17 and Table 3.3.

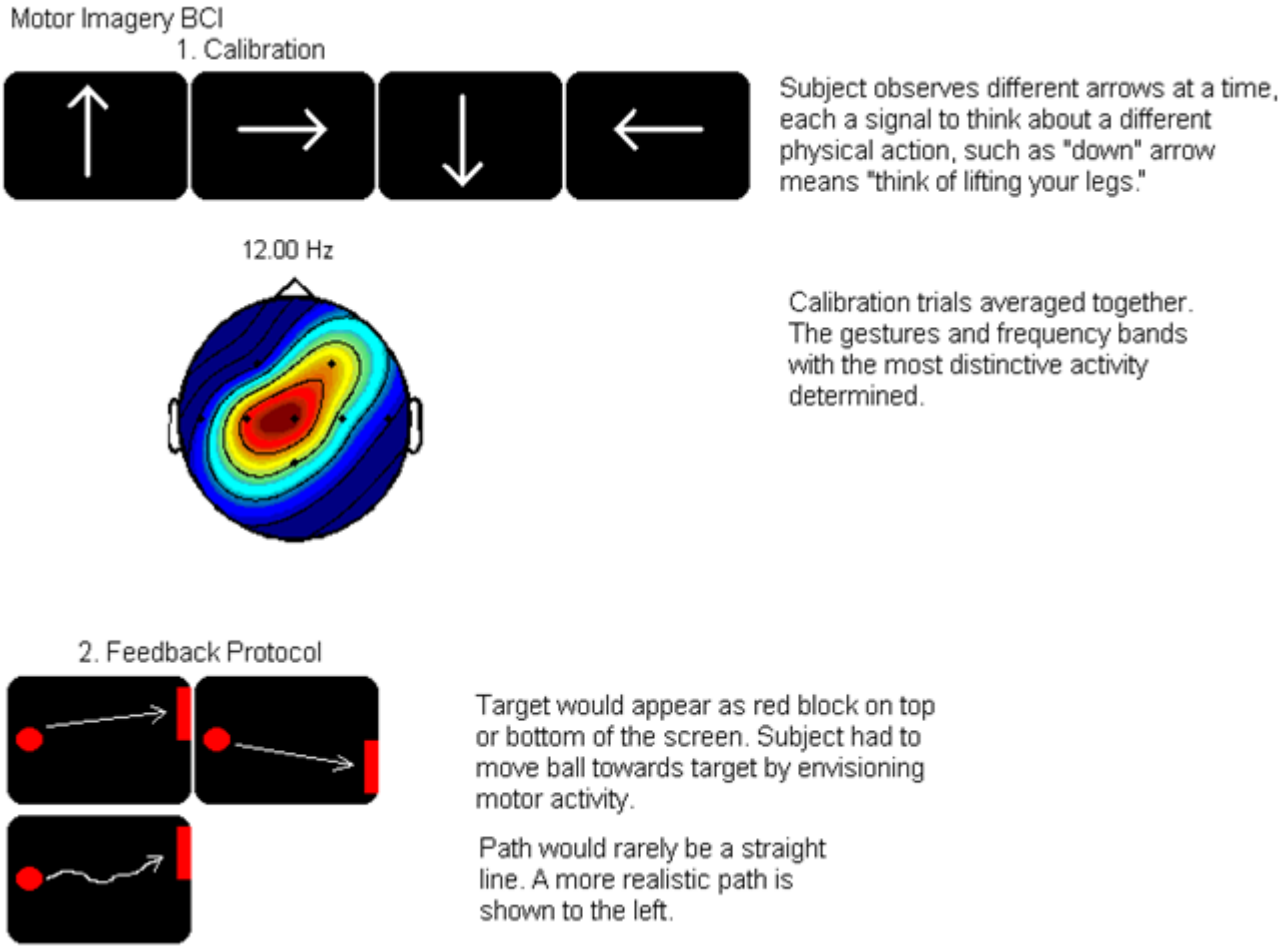


Figure 3.17: Motor Imagery BCI Overview

After calibration, a subject was tested in the protocol. After the start of each test, a delay of 1 second was inserted before the target appeared. The target, a red box, appeared on the upper or lower half of the right side of the screen. A second later, the cursor appeared in the form of a red ball. The ball had an initial (and constant) velocity, and traveled across the screen from the left to the right. The subject then attempted to use motor imagery to guide the path of the ball before it made contact with the right side of the screen. The subject's cursor movement process took approximately 7 seconds. After the cursor reached the side of the screen, another delay of 1 second was inserted. If the cursor made contact with the target, both briefly flashed yellow.

Following both objects flashing, the screen became blank, and the trial concluded. The target then reappeared after 2 seconds. An individual trial took approximately 12 seconds.

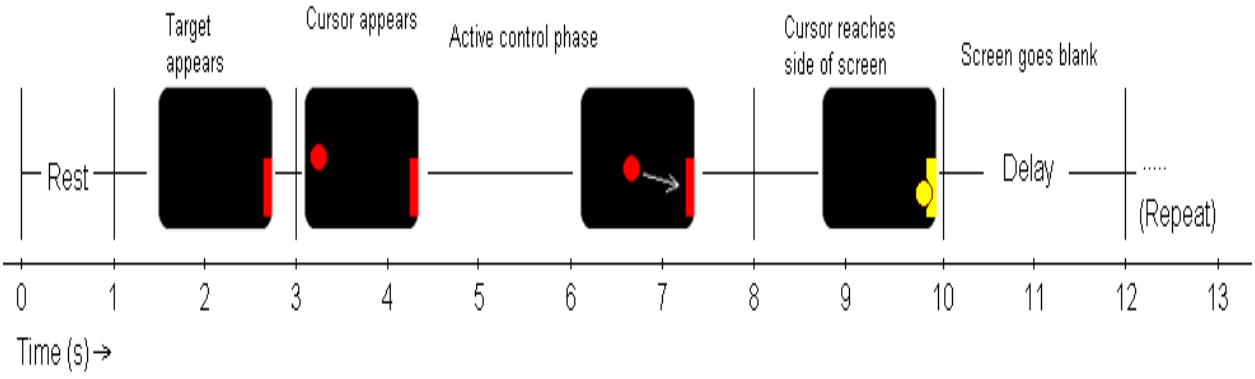


Figure 3.18: Motor Imagery BCI Sequence

Twelve sessions were conducted, with a total of eighteen trials conducted per session. The protocol required a total of 206 trials. Of the total number, 36 trials were considered practice trials; these trials were discarded. Performance on the remaining 180 trials was recorded. The protocol was then repeated with distraction for an equal number of sessions. The only difference for the subject was the distracting sounds added (e. g. loud noises, recorded voices, and animal sounds). A summary of the protocol appears below in Figure 3.19.

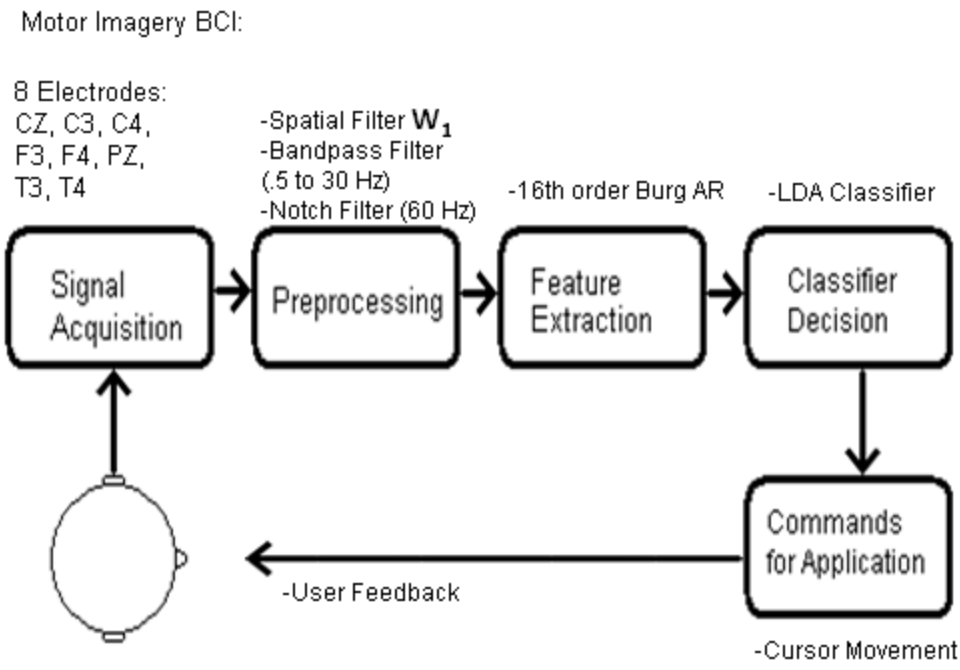


Figure 3.19: Motor Imagery BCI Summary

3.2.1.2 P300 SETUP AND CALIBRATION

The P300 virtual keyboard protocol uses an evoked feature in EEG signal known as the P300 wave [**1**]. In the P300 speller protocol, the P300 is used to control a virtual keyboard, shown in Figure 3.20.

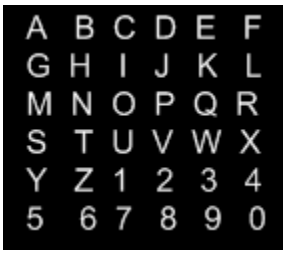


Figure 3.20: Sample P300 Virtual Keyboard

Calibration was essential for the P300 speller protocol [**13**]. Twenty trials were averaged for each character, as shown in Section 2.1. A window of 800 ms was used, which started after each

stimulus. Calculations were performed in the spatio-temporal domain. For calibration, the subject was instructed to focus on the character he or she wished to select, and count the number of times that it flashed. The subject was first instructed to spell the word "THE." The target word was changed to "QUICK." The third word was "BROWN." The final word was "FOX." The letters were far apart in position on the matrix, so the subject had to focus on different letters. During the calibration session, subject control was optimized. The expectation for the subject was that no correct characters were selected without calibration. Hence, calibration is necessary for each person. The P300 feature is known to be less apparent in older individuals (age>65 years old) [**36**], which is why younger subjects were preferred for the study.

The recorded P300 trials were subjected to offline processing to find subject-specific parameters. Offline processing averaged trials together to determine a subject specific threshold. The threshold was applied by the means of an 8 x 8 spatial filter $\mathbf{W_2}$, with weight vector for each electrode, **w**, computed using FLD, as shown in Section 2.1. An example of spatial filter $\mathbf{W_2}$ is shown below in Figure 3.21.

Weight Matrix $\mathbf{W_2}$

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8
19.5915	-3.8014	-4.0093	-22.136	-6.2015	-3.937	2.9095	-14.736
9.8943	8.684	7.4512	-6.7296	-15.3089	-9.4582	12.161	-0.295
-11.463	-19.546	-2.3105	0.3356	1.7608	-18.945	-1.9511	3.9809
6.9207	0.2466	-1.7804	-0.1587	-26.099	8.4091	-6.0077	6.3818
-16.0508	5.7455	6.6012	-9.6291	8.4196	-1.541	-20.817	8.9163
7.44	-0.7839	5.5637	6.921	7.5753	3.6955	-2.0936	6.6562
-1.6153	-1.2251	-2.9784	4.7627	8.6386	-20.57	1.1976	10.056
-4.044	-0.1299	4.198	-3.8353	15.197	14.025	-19.521	-4.414

Figure 3.21: P300 Spatial Filter Example

Two categories were established during offline processing: attended stimulus and unattended stimulus. The attended stimulus was an average of all the times the "correct" row or column flashed. The unattended stimulus was an average of the time the "incorrect" or undesired rows and columns flashed. For example, if the subject was trying to select the letter "T" in the word "THE," anytime a row or column other than that included "T" flashed was an "incorrect" flash. Obviously, the protocol included more "incorrect" stimuli than "correct" ones. The averaged time-domain signals were used to select each subject's optimal features. The averaged features and spatial filter allowed the subject to control the P300 speller [**1**]. Calibration data was temporally averaged; FLD computed the spatial filter $\mathbf{W_2}$ that separated the attended stimulus and unattended stimulus, and the weight matrix was used to set up an LDA classifier, as shown in Section 2.2. A summary of the calibration process is shown in Figure 3.22 and Table 3.3.

After calibration, the subject had to spell out five separate words: HI, CAB, FOX, DOGS, and JUMPS. The subject was able to backspace to remove incorrect characters, and was given two attempts to spell the word correctly. If after six incorrect characters were selected consecutively, then the subject either had to try again or move on to the next word. If the subject wished to try again, all characters were erased, and the subject had one more chance. After two attempts at any word, the subject had to move on to the next one. For the P300 spelling protocol, the electrodes F3, F4, T5, T6, C3, C4, CZ, and PZ were used. The electrodes T5 and T6 were used due to the P300 originating near the visual cortex [**35**].

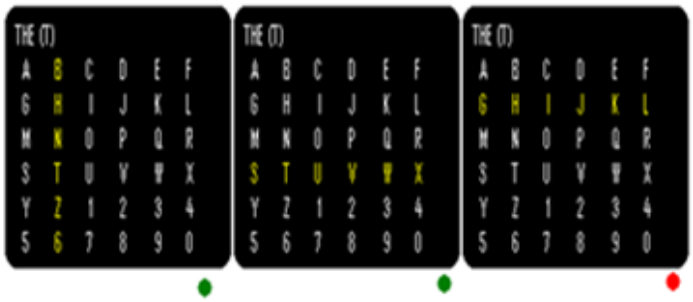
The P300 speller required spatial filtering specific for each subject. The spatial filter $\mathbf{W_2}$ was an 8 x 8 matrix consisting of individual weight vectors $\mathbf{W_2} = [\mathbf{w_1}, \mathbf{w_2}, \ldots., \mathbf{w_8}]^{\boldsymbol{t}}$ computed using FLD that separated the P300 peak from background noise in the EEG. An example of spatial filter $\mathbf{W_2}$ is shown.

Each spatial filter was calculated by averaging the calibration trials together to find coefficients that formed subject specific thresholds, which were optimized by FLD, and used for an LDA classifier. With successful calibration, the spatial filter $\mathbf{W_2}$ allowed the subject to select one of the 36 characters. A 1-second delay occurred between the selection of characters. Before a character was selected, all rows and columns flashed approximately 20 times in random sequence. Each flash was 150 ms in duration. The flashing stimulus was followed by a 2 second delay in between when a character appeared, and when selection for the next trial started. The 2 second rest allowed subjects to blink or swallow if necessary.

Part A: P300 Speller Examples

P300 Speller BCI

1. Calibration

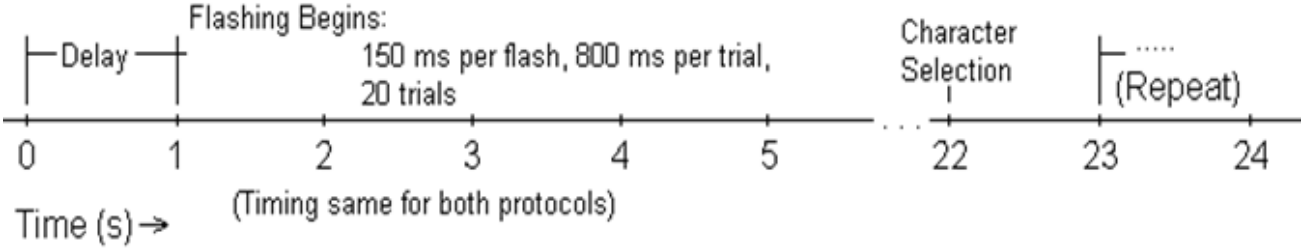


For calibration, the subject was asked to count whenever the row or column of the letter in parenthesis flashed (denoted by green circles), and ignore all other cases (denoted by red circles). Note the circles did not appear in the protocol.

2. Free Spell

After calibration, the subject was charged with the 'free spell' of a particular word. A backspace option was present to remove an incorrect character (e. g. "T" when trying to spell "CAB"). The "BS" in the lower right corner of the screen was selected as any other character, and removed the previously entered character.

Part B: Time Line



Part C: Word Order

Calibration Word Order:

THE	THE	QUICK	QUICK	BROWN	BROWN	FOX	FOX

Free Spell Word Order:

HI	FOX	CAB	DOGS	JUMPS

Figure 3.22: P300 Speller Overview

With the total number of delays and flashing stimuli, a single character required approximately 22 seconds to select and enter. The first session, the word “HI,” was used as a practice session and not included in final results. The protocol was repeated with exactly the same conditions as before, adding only the same distractions as the motor imagery protocol. A summary of the protocol is in Figure 3.23.

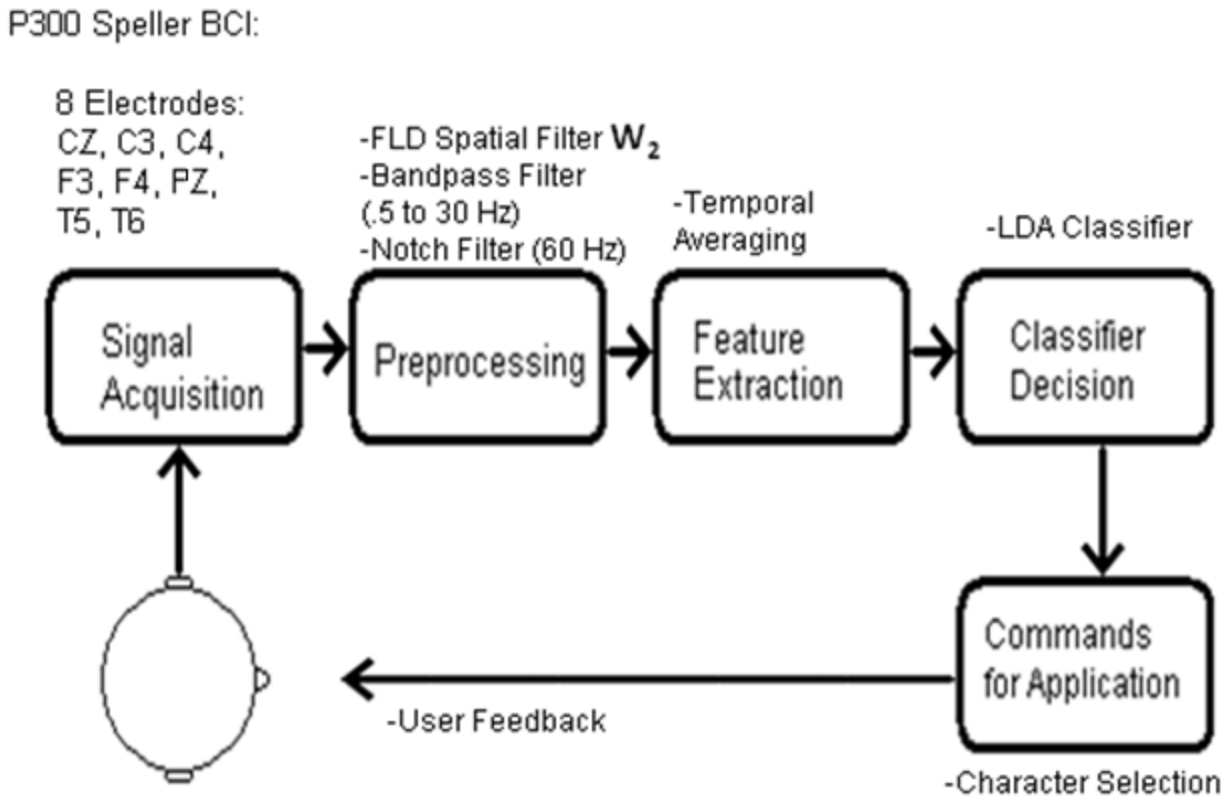


Figure 3.23: P300 Speller BCI Summary

Table 3.3: *BCI Calibration Summary*

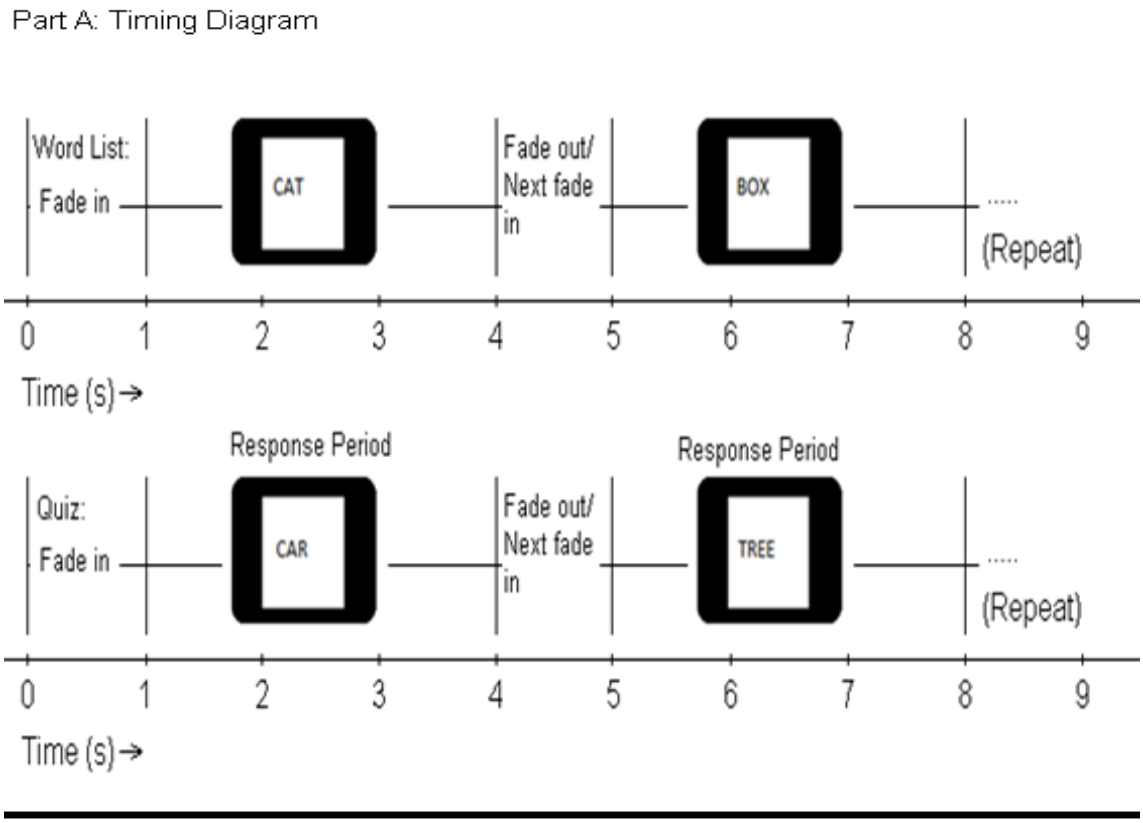
BCI Calibration Steps
Motor Imagery Protocol: 1. Take data from training protocol. 2. Average training epochs together, as shown in Section 2.1. 3. Calculate Burg AR coefficients for time series *x(n)*, as in Section 2.1. Set model order *M*, initialize sample index at *n*=0. Calculate optimal reflection coefficient for each value of *m*. Calculate vector **a**(*m*). 4. Compare spectral coefficients for each "gesture" to find highest amplitudes. 5. Set threshold with respect to highest spectral amplitude.
P300 Speller Protocol: 1. Take measurements from training protocol. 2. Average training epochs together, as shown in Section 2.1. 3. Perform FLD to compute weights **w** for each channel, as in Section 2.1. Determine optimal decision boundary between classes. 4. Weights in **w** used to set up LDA classifier for individual channels.

3.2.2 MEMORY AND FOCUS PROTOCOLS

3.2.2.1 VERBAL LEARNING TASK

The verbal learning task was based on a commonly used memory testing protocol [**37**]. In the verbal learning task, participants saw a list of 15 words. Each word appeared on the screen for 4 seconds, and faded out before the next word appeared. Only one word was ever present on the screen at a time. Each word faded in and out for 300 ms each.

The volunteer had to remember the words. At intervals of 2 minutes, 20 minutes, and 24 hours, the participant was tested on the words he or she was shown. At each interval, the subject was shown a test list of 10 words. Each word was shown on the screen for 3 seconds, before showing the next one. The subject had to determine which of the words were from the original list, and which were not on the list.



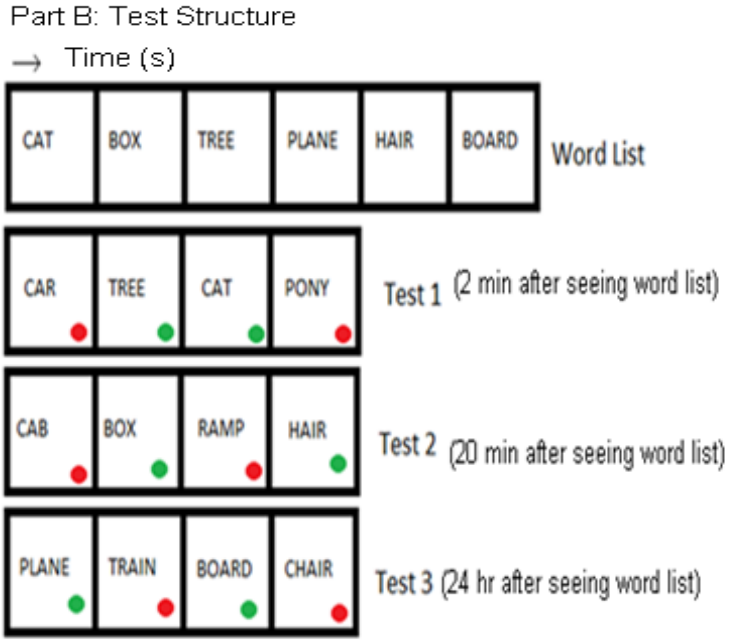


Figure 3.24: Verbal Learning Task

Each list had five random words from the original list and five new words. If the subject saw or recognized a word that was on the original list, he or she was asked to press a button marked “1.” If the word shown on screen was not on the origin list, a button marked “2” was pressed. No word from the original list or test lists was repeated within the same trial or on others. The short term (2 minutes) test was a test for short-term memory. The second interval test (20 minutes) and third interval test (24 hours) were intended to test long-term memory. In Figure 3.24 above, a green circle indicates the word was on the original list (indicating Button 1 should be pressed), and a red circle shows the word was not on the original list (indicating Button 2 should be pressed). The circles were not present in the protocol, but instead added to Figure 3.24 to indicate the correct responses.

3.2.2.2 N-BACK TEST

The second protocol tested for both functional short-term memory and focus was the N-back test [**26**]. The N-back test involves a task that requires a participant to maintain focus and remember a certain number of characters. A sequence of letters is shown to a participant. Each letter is shown on the screen for only 3 seconds, and each letter is always displayed alone. Each letter fades in and out for 300 ms each. If a letter repeated a certain number of times based on the test, the subject had to press a button.

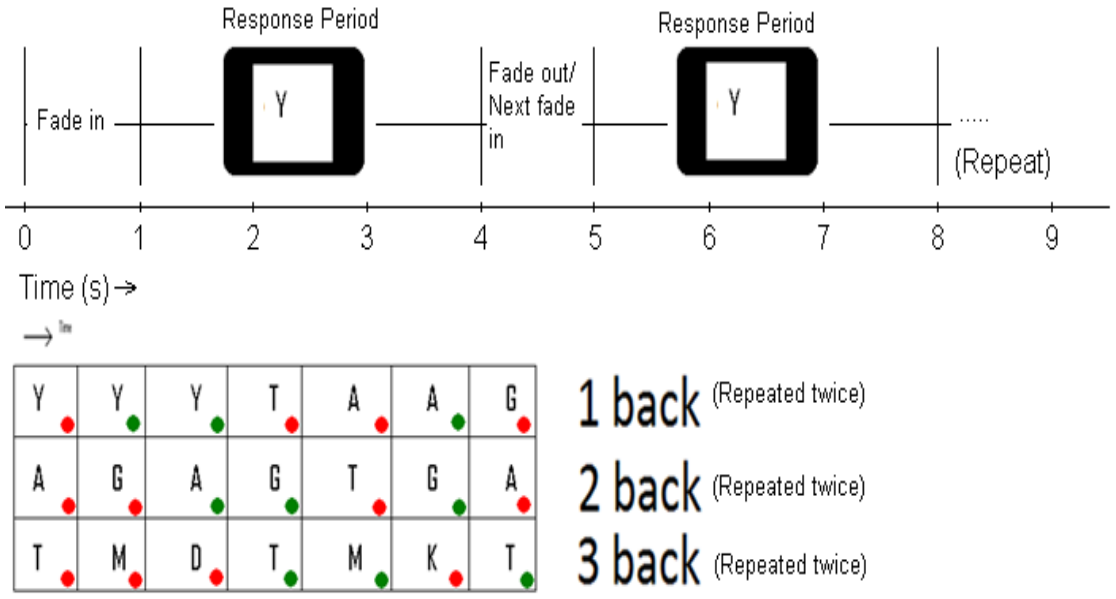


Figure 3.25: N Back Test

In Figure 3.25, the green circles indicate when a button should be pressed for each test, and the red circles indicate when a button should not be pressed. The circles were not present in the protocol, and they show only the correct responses on the example. A 0-back test (not used in this study) consisted of a subject pushing the button at a pre-specified character on screen (e. g. the letter "X"). A 1-back test requires the subject to push the button after seeing the same letter consecutively. A 2-back test requires the subject to push a button if a letter repeats after one consecutive character. An example of a 2-back test is the sequence "G-T-G," where the subject pressed the button after the second letter "G" appeared on screen. A 3-back test requires the subject to press the button if a letter repeats after two other characters. An example of a 3-back test is the sequence "T-M-K-T," where the subject pressed the button when the second "T" appeared on screen. The N-back test compares focus and short term memory. The protocol used in the study consisted of two 3-back tests, two 2-back tests, and two 1-back tests in random

order. A practice session was included for the test. Each type of test was scored independently from the others.

3.2.3 PERFORMANCE CRITERIA

Different performance criteria were employed for each protocol. For the verbal learning task and N-back tests, many of the same criteria were used. The sensitivity, precision, negative predictive value, and accuracy of each were calculated. In the case of the N-back tests, the performance values for each test were computed separately. For the motor imagery task, only accuracy was used. For the P300 spelling paradigm, the accuracy and information transfer rate was found. To compute each of the performance criteria, the following equations were used.

In equations below, *TP* is True Positive, or number of times a positive result is correctly identified; *TN* is True Negative, or number of times a negative result is correctly identified; *FP* is False Positive, or number of times a positive result is incorrectly identified; *FN* is False Negative, or number of times a negative result is incorrectly identified; and *N* is the number of classes or possible targets. All of the measures are expressed as a percentage.

S is sensitivity, also known as recall [**30**], and ability of the test to find correct positive cases.

$$s = \frac{TP}{(TP+FN)} \tag{3.1}$$

P is the precision, or number of true results in the positive population, both correct and incorrect.

$$P = \frac{TP}{(TP+FP)} \tag{3.2}$$

A is accuracy, or percentage of positive and negative tests correct.

$$A = \frac{(TP+TN)}{(TP+TN+FN+FP)} \tag{3.3}$$

SPC is specificity, or how well the test detects true negative cases.

$$SPC = \frac{TN}{(TN+FP)} \tag{3.4}$$

NPV is negative predictive rate, or how likely the system was to give a negative result.

$$NPV = \frac{TN}{(TN+FN)} \tag{3.5}$$

Two non-percentage measures were introduced. The *BR* is the bit rate or the total bits transferred.

$$BR = log_2N + Alog_2A + (1-A)log_2(\frac{(1-A)}{(N-1)}) \tag{3.6}$$

ITR is the information transfer rate, or total number of bits transferred over a unit of time. It is especially relevant to a P300 speller, rather than a motor imagery BCI. *TD* is trial duration, or time to select a character, in minutes.

$$ITR = \frac{BR}{TD} \tag{3.7}$$

The units of the ITR are bits per minute, a commonly used measure of P300 BCI performance. A higher ITR means more information and commands were transferred over a period of time [**38**].

Each protocol used the performance criteria relevant to the specific protocol. The results for each protocol were analyzed separately from other protocols. The accuracy, sensitivity, precision, negative predictive value, and true negative rate were used for the verbal learning task and N-back protocols. The P300 speller protocol originally used the accuracy and *ITR*.

Some of the criteria were changed. Many of the performance statistics had become redundant. Accuracy proved to be a better metric for measuring the performances on the verbal learning task and N-back test. Accuracy was used for the verbal learning task, N-back protocol, motor imagery BCI, and P300 speller. The specificity, precision, sensitivity, and negative predictive rate were removed.

Applying true positive, true negative, false positive, and false negative conditions was impractical for the motor imagery BCI and P300 speller. Due to the extreme unlikelihood of an accidental backspace in the P300 speller, establishing true positive, true negative, false positive, and false negative conventions was impractical. Only accuracy and bit rate were used for the P300 speller.

3.2.4 EXPERIMENTAL SCHEDULE

After simplifying performance measures, the experimental schedule of protocols was organized. For the initial study, volunteers untrained in BCI were recruited. The participants had little or no prior experience with meditation. The non-meditation group of participants made up the control group. The volunteers who had been practicing meditation for at least a month comprised the meditation group. A schedule of the experiments is shown below in Table 3.4.

Table 3.4: *Experimental Schedule*

Subject Protocol		
Day 1	Duration (min)	Activity
	20	EEG cap placement
	10	Motor imagery calibration
	3	Break
	20	P300 calibration
	5	Break
	3	Show verbal learning task list
	3	Subject word memory test (short term)
	5	Break
	15	N back test including a practice run
	3	Break
	3	Subject word memory test (long term)
	5	Break
	15	6 sessions of 18 cursor/motor imagery trials (the first two are practice)
	5	Break
	15	6 sessions of 18 cursor/motor imagery trials
Day 1 Total	130	Hours: 2.166667
Day 2		Activity
	20	EEG cap placement
	3	Subject word memory test (24 hour memory)
	5	Break
	20	P300 tests: spell: HI, FOX, CAB, OVER, JUMPS (HI is practice word)
	5	Break
	15	6 sessions of 18 cursor/MI trials with distraction (first two are practice)
	5	Break
	15	6 sessions of 18 cursor/motor imagery trials with distraction
	5	Break
	20	P300 tests: spell: HI, FOX, CAB, OVER, JUMPS w/distraction (HI is practice.)
Day 2 Total	113	Hours: 1.883333
Total	243	Hours: 4.05

Based on input from a psychologist, the experiments were conducted over two consecutive days. Certain tests were moved to a second day so the subject was not overwhelmed or fatigued after a single long day. The total time required on each day was rounded to approximately 2 hours. Breaks were also added to ensure a participant could mentally recover between tests. During breaks, a subject was able to use the restroom, talk freely, relax, stretch, check their phones, have refreshments, and briefly use the Internet. The subject was asked to turn off or silence personal electronic devices before setup.

The largest time requirement on both days was the setup time. Depending on any perspiration, hair length, hair gel, or other factors, the electrolyte gel may or may not rapidly make a low-impedance connection. Connecting a participant ranges in time from 10 minutes to half an hour. Setup sometimes extended the total length of the experiment. On both days, the estimated preparation time of 20 minutes was assumed.

After setup, the subject underwent calibration for both the motor imagery and P300 protocols. The first calibration session was for motor imagery. The participant underwent two sessions of the motor imagery calibration session before the first break. Following completion of the first calibration session, a longer calibration session took place. The participant was asked to spell each of the following words on the P300 speller twice: THE, QUICK, BROWN, and FOX. After a quick break, the participant underwent the verbal learning task protocol.

The participant was shown the list of 15 words. After 2 minutes, the participant was given the first test. After the first verbal learning task (VLT) quiz at 2 minutes, the subject took a break. Then, the participant received instructions regarding the N-back test, and was given a practice

form of the N-back test. The subject took another break, and the N-back test was given. While the subject was taking the N-back tests, calibration data for the BCI protocols was used to calibrate the motor imagery and P300 speller protocols. After a quick break, the participant was given the second VLT quiz, the 20-minute test.

After another break, the participant began the motor imagery BCI without distraction. After six sessions, the participant was given another break. After 12 motor imagery sessions were completed, the participant finished the first day.

The second day started with the third and final VLT quiz at 24 hours. After a break, the participant used the calibrated P300 speller without distraction. After the P300 speller sessions without distraction were concluded, the participant was given a break. After the break, the participant was given noise-canceling headphones through which the distracting sounds were played. The next protocol used was motor imagery with distraction. After 6 sessions, the participant was given a break. After the break, six final sessions of the motor imagery BCI were performed. A short break was given to the participant. After the final break, the final protocol was used, P300 speller with distraction. Following the conclusion of the final protocol, the second day of testing was over for the participant. The schedule was repeated on every subject in both the control and meditation groups. After data from all 20 participants were collected, they were analyzed using mixed model ANOVA (analysis of variance), as detailed in Section 2.3.

3.2.5 ANOVA ANALYSIS SETUP

Each protocol had its own analysis performed independently of the other protocols. A 95% confidence interval was used for each analysis. The following is the definition of the between-subjects comparison between the meditation and control groups. The variable $\mu_{Control}$ is the

mean group accuracy for the control group. The variable $\mu_{Meditation}$ is the mean of accuracy for the meditation group.

$$H_{01}: \quad \mu_{Control} \geq \mu_{Meditation} \tag{3.8}$$

$$H_{a1}: \quad \mu_{Control} < \mu_{Meditation} \tag{3.9}$$

For the verbal learning task, a 2 x 3 mixed model with two factors was required. The first factor was group (control or meditation) as the between-subjects factor. Since the test was a comparison of long-term and short-term memory, the different time intervals (2 minutes, 20 minutes, 24 hours) formed the second, within-subjects factor.

$$H_{02}: \quad \mu_{2min} \geq \mu_{20min} \geq \mu_{24hour} \tag{3.10}$$

$$H_{a2}: \quad \mu_{2min} < \mu_{20min} < \mu_{24hour} \tag{3.11}$$

ANOVA tested for significant differences in both groups over time, as well as interaction between both factors. The number of words remembered and correctly identified was believed to drop over time. A hypothesis is that the meditation group had significantly better performance over the long term than the control group.

For the N-back protocol, a 2 x 3 mixed model ANOVA was used. The between-subjects factor was group (meditation and control), and the within-subjects factor was type of test (1 back, 2 back, or 3 back). Significant differences in performance meant that one group has better focus on certain tasks than others.

$$H_{02}: \quad \mu_{1back} \geq \mu_{2back} \geq \mu_{3back} \tag{3.12}$$

$$H_{a2}: \quad \mu_{1back} < \mu_{2back} < \mu_{3back} \tag{3.13}$$

The hypothesis is that the meditation group should have significantly better performance on the more difficult tests, especially the 2 back and 3 back, than the control group.

The motor imagery analysis included both the non-distraction and distraction conditions. There were 180 trials over 10 sessions of 18 trials. A 2 x 2 mixed model was used. The between-subjects factor was group (meditation or control), and the within-subjects factor was the presence of distraction (normal conditions against distractions playing). Since proficiency with a motor imagery BCI can take significant training time, the sessions were averaged together. The changes reduced the mixed model to 2 x 2 ANOVA.

$$H_{02}: \quad \mu_{Distraction} \geq \mu_{NoDistraction} \tag{3.14}$$

$$H_{a2}: \quad \mu_{Distraction} < \mu_{NoDistraction} \tag{3.15}$$

The hypothesis is that the meditation group should perform significantly better than the control group in both cases.

The P300 speller used a 2 x 2 mixed model. The between-subjects factor was the group and the within-subjects factor was the session. The protocol had four sessions, each a separate word: CAB, FOX, DOGS, and JUMPS. Performance across sessions was averaged due to small number of trials.

$$H_{02}: \quad \mu_{Distraction} \geq \mu_{NoDistraction} \tag{3.16}$$

$$H_{a2}: \quad \mu_{Distraction} < \mu_{NoDistraction} \tag{3.17}$$

Both accuracy and information transfer rate were used as performance measures for the P300 speller protocol. The hypothesis was that the meditation group would have significantly better performance than the control group. The results of the tests are displayed in Section 4.

CHAPTER 4: RESULTS

Ten subjects were tested per group. Subject accuracy on the four primary protocols was the primary performance measure. Other performance measures (e. g. sensitivity, specificity, negative predictive rate, information transfer rate, and positive predictive rate) were computed. However, they provided no additional information regarding significant differences between meditation and control group performances. Average performance results and variances are displayed in this section.

4.1 VERBAL LEARNING TASK RESULTS

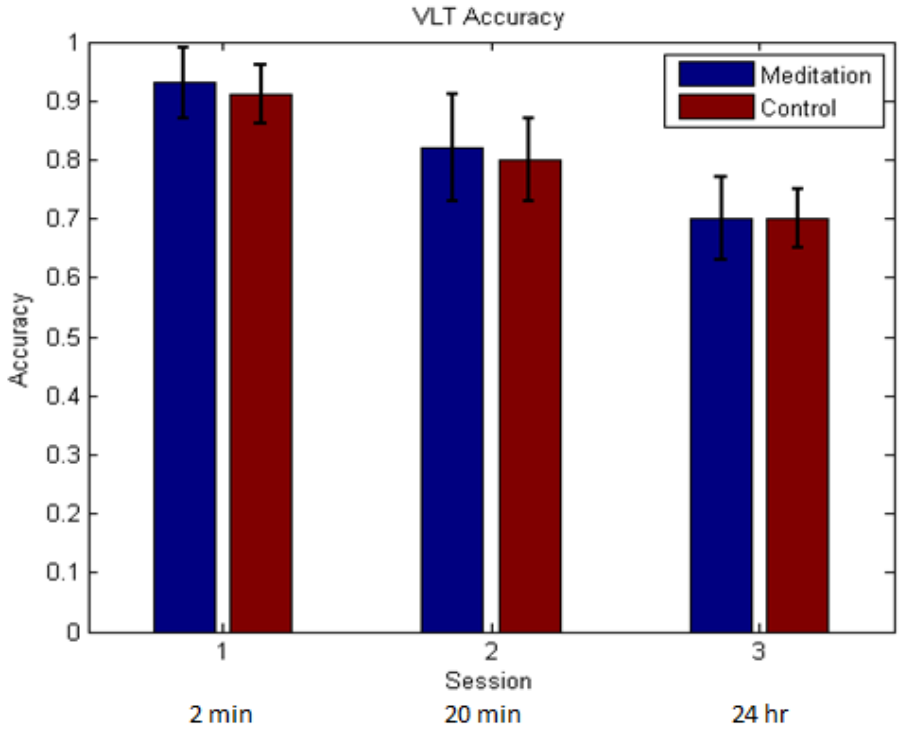


Figure 4.26: Average VLT Accuracy Over Time

In the Verbal Learning Task (VLT), the differences between the meditation group and control group was not significant ($F(1,18)=0.202$, $p=0.659$). Significant differences were found for time

($F(1,18)=69.7$, $p=<.000$); however, with performance dropping in each successive test, the drop was expected. The interaction between the factors was not significant ($F(1,18)=.062$, $p=.94$). The meditation group and control group both scored close to each other, and no significant differences were detected for any parameter. Analysis showed a significant drop in performance over time, primarily between the 2- minute and 24-hour tests. The decrease in performance reflects subjects forgetting the word list over time.

4.2 N-BACK TEST RESULTS

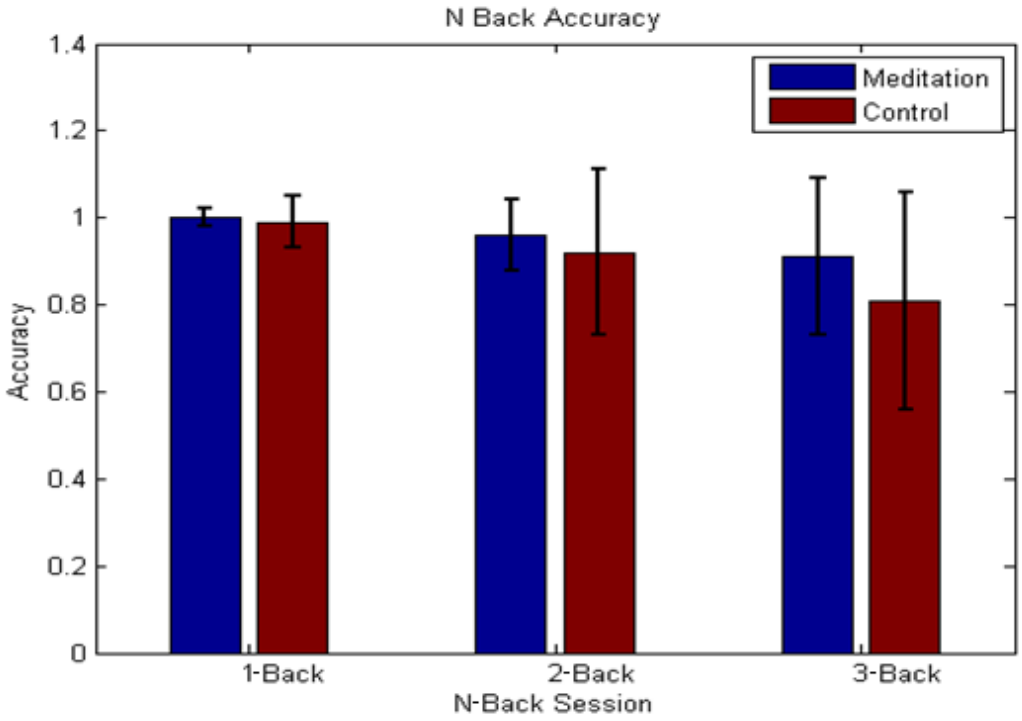


Figure 4.27: Average N Back Results Over Time

For the N-back test, differences between the meditation group and the control group was not significant ($F(1,18)=3.164$, $p=0.092$). Differences in performance between test types was significant ($F(1,18)=31.67$, $p<.000$). The interaction between type of test and group was not

significant ($F(1,18)=2.623$, $p=.086$). Performance averages still do show a slightly widening gap in performance. A drop in performance occurred as the number of characters in the test increased, notably between the 1-back and 3-back tests. With a p value of .092, the difference between the meditation and control groups was significant with a 90% confidence interval.

4.3 MOTOR IMAGERY BCI TEST RESULTS

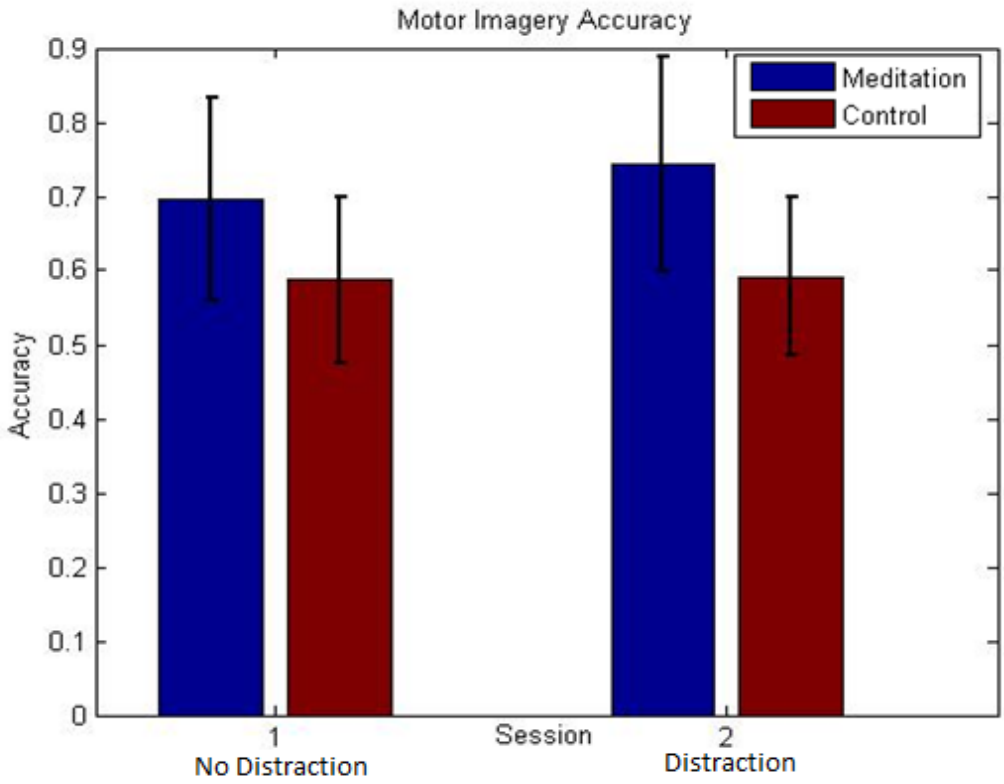


Figure 4.28: Average Motor Imagery BCI Performance

For the motor imagery BCI, the difference between groups was not significant ($F(1,18)= 2.628$, $p=.122$). Distraction did not significantly affect performance ($F(1,18)=2.414$, $p=0.138$). The interaction between both was not significant ($F(1,18)=1.617$, $p>.05$). The bars labeled "*Session 1*" show the averaged results of the "*no distraction*" case, with meditation on the left and control

on the right. The bars labeled "*Session 2*" show the performance of both groups for the "*distraction*" case. Individual subjects generally scored consistently across time. Variances were high for both groups, as the figures show. Some subjects were BCI illiterate for the motor imagery protocol, as shown by lack of control. Of note are some subjects who were proficient at the protocol and not the P300 speller, and vice versa. Meditation group performed higher on average than control, although there were no significant differences. No significant changes across time were measured.

4.4 P300 SPELLER BCI TEST RESULTS

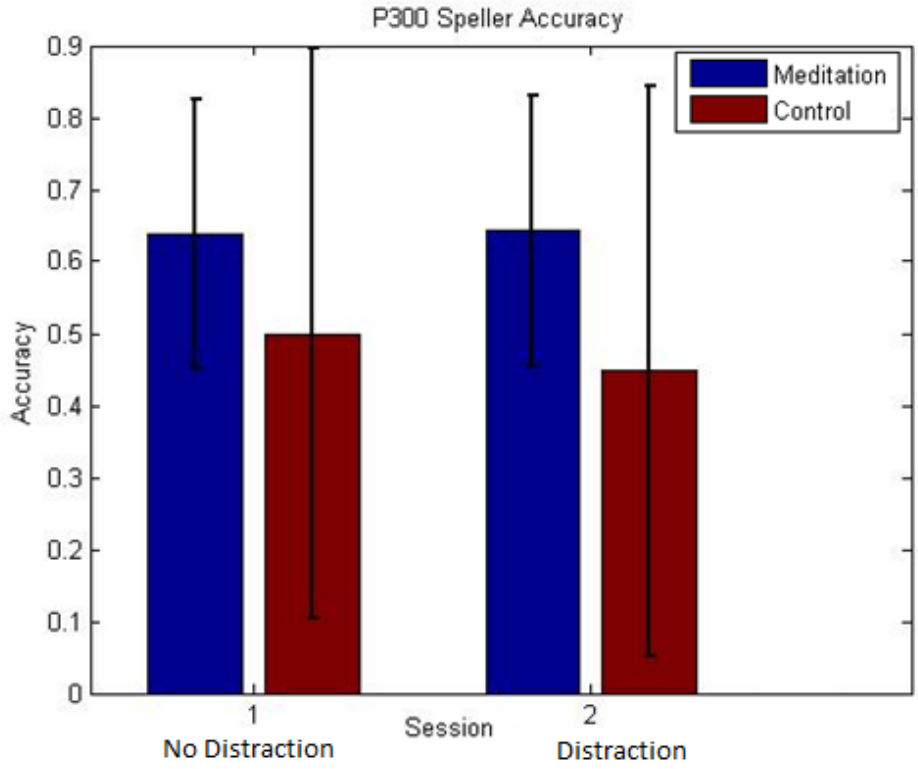


Figure 4.29: Average P300 BCI Performance

Results for the P300 speller were similar to the motor imagery results. The bars labeled "*Session 1*" show the averaged results of the "*no distraction*" case, with meditation on the left and control

on the right. The bars labeled "*Session 2*" show the distraction between two groups for the "*distraction*" case. No significant difference in performance was found between both groups ($F(1,18)=1.364$, $p=.258$). The effects of distraction were not significant ($F(1,18)=.433$, $p=.519$). The interaction between both was not significant ($F(1,18)=.151$, $p=.703$). Analysis revealed no significant difference in performance between groups, no difference due to distraction, and no difference across time. On average, performance scores were lower for the P300 speller protocol than for the motor imagery protocol. Since accuracy is directly related to the information transfer rate, the findings for accuracy were consistent with the ITR. No significant difference was found for information transfer rate, although the meditation group scored consistently higher. With a maximum information transfer rate of about 11.3 bits per minute, the value is reasonable for such a system [**39**]. The variance of the ITR for each group was also large. The P300 speller BCI protocol had much longer trial and interval times than others, limiting the information transfer rate compared to other protocol. The greater number of sub-trial flash events makes a single artifact-filled trial less likely to affect the results. More P300 events must be averaged.

Table 4.5: *Experimental Results*

Protocol		Meditation		Control			
VLT		**Mean**	**Stan Dev**	**Mean**	**Stan Dev**	**p**	**F(1,18)**
	2 minutes	0.93	0.094868	0.91	0.073786	**Group**	0.659
	20 minutes	0.82	0.147573	0.8	0.11547	**Time**	<.000
	24 hour	0.7	0.11547	0.7	0.08165		
		Mean	**Stan Dev**	**Mean**	**Stan Dev**	**p**	**F(1,18)**
N Back	**1 back**	1	0	0.995	0.010541	0.092	3.164
	2 back	0.9855	0.025653	0.9355	0.071237	<.000	31.67
	3 back	0.945	0.092646	0.798	0.107166		
		Mean	**Stan Dev**	**Mean**	**Stan Dev**	**p**	**F(1,18)**
MI BCI	**No Distraction**	0.686467	0.201957	0.592	0.145346	**Group**	0.122
	Distraction	0.724033	0.214096	0.597917	0.139932	**Distraction**	
		Mean	**Stan Dev**	**Mean**	**Stan Dev**	**p**	**F(1,18)**
P300 BCI	**No Distraction**	0.638228	0.30567	0.469898	0.374519	**Group**	0.258
	Distraction	0.62438	0.314591	0.389877	0.415473	**Distraction**	

CHAPTER 5: DISCUSSION

5.1 SUMMARY OF ACCOMPLISHMENTS

Over the course of this study, several protocols were analyzed. An effect of meditation on BCI and memory was examined. Experimentation on the limited size cohort showed that there was no significant benefit to long-term or short-term memory in the verbal learning test applied. A potentially significant difference was detected on the 3-back test. With a *p* value of .092, the difference between the meditation and control groups was significant with a 90% confidence interval. The value may be due to variance amongst subjects, but most likely due to the small sample size available to the study. The meditation group consistently performed higher on average than the control group in the 2-back and 3-back tests. Both the motor imagery BCI and P300 speller protocols had the meditation group average performance was higher than the control group, with no significant differences between them. Also for BCI protocols, no significant differences were detected in the presence or absence of distraction. Despite no significant differences in results, the small sample size and variety of subject backgrounds requires further experimental confirmation. If the study was repeated with a larger sample (>20 participants per group), and the variances remained consistent across each group, significant differences may be present. The study was also the first to investigate the possible use of meditation to improve subject control of a P300 speller protocol.

5.2 POSSIBLE SOURCES OF ERROR

The preprocessing techniques in EEG should not distort the data. All non-BCI protocols were both manually and automatically graded and verified. EEG is innately susceptible to noise and artifacts. Artifacts and noise from motion, muscular action, and ocular activity can distort EEG recordings. Participants sometimes became uncomfortable, so they started to shift around slightly. Participants were instructed to restrict motions of the body, eyes, and head as much as possible. Breaks were given to prevent the subject from becoming too uncomfortable. Times for subjects to blink or move their heads if necessary were factored into most protocols over 4 minutes in length.

Some settings of the BCI system had been modified to achieve greater control. The system had significant latency in the case of the P300 speller. For all calibration data, the spikes occurred approximately 400 milliseconds later than the expected value. Since the P300 by definition occurs at approximately 300 milliseconds, a delay of the feature by 400 milliseconds was likely due to latency within the system. A number of faster computers, system configurations, and other techniques were tried, but the issue remained. By extending the epoch length to 800 milliseconds, system latency was counteracted.

Calibration was a significant part of the experiment, and a likely source of error. While the motor imagery protocol was robust with regards to calibration, the P300 speller was not. A subject may incorrectly focus or be in an inattentive state, and the calibration may not function properly. Improper calibration can produce incorrect results in the P300 speller even if the subject is

following proper technique. Subjects may also unwillingly blink or move muscles, causing EMG noise or artifacts [**10**].

Even though a participant may state he or she is awake, the individual may be forcing himself or herself to stay awake and aware. While the level of awareness of a subject can vary, the subject should arrange for the study to be conducted during free time, or times free from stress. Stimulant drugs or foods should not be issued to the subjects. A chance existed that a subject consumed a sugary or caffeine-rich food during a break or prior to the study. Any stimulants took a significant amount of time (>20 min) to go into effect [**7**]. The small population size prevented a more conclusive study. BCI illiteracy was another source of error; some subjects were simply unable to control certain protocols. While some subjects could control one protocol and not the other, insufficient data exists to make any significant observations.

5.3 RECOMMENDATIONS FOR FUTURE WORK

This study includes several venues for possible improvement. One possible improvement is a larger sample size (>20 participants per group). If a larger group of individuals skilled with mental training can be recruited, then the study may establish more certain results across a larger group. A primary way to improve the experiment was the recruitment of an equal or greater number of individuals instructed in the same style of mental training. More consistency would be introduced upon the members of the meditation group. In other studies, more experienced meditation practitioners from the same background were recruited [**5**] [**29**]. Subjects with the same form of meditation or relaxation techniques, whether Zen meditation, yoga, progressive muscle relaxation, or Transcendental Meditation, could eliminate the confound arising from different styles being brought together and placed in the same category.

Another possible method of improvement is to use more electrodes, develop a new spatial filter to improve spatial resolution, or both. The changes could improve spatial resolution, and allow for more distinctive features to be generated. A possible drawback is longer preparation time due to use of more electrodes. A spatial filter alone could improve resolution and increase the signal to noise ratio without a longer preparation time. More electrodes and a new spatial filter could benefit the motor imagery task and the P300 speller. Since only eight electrode channels were used to record, spatial resolution was lower. More channels and an improved spatial filter could be used to improve spatial resolution [**4**]. Adding an automated system to remove motor and ocular artifacts may also improve the signal quality. Some BCI protocols train with artifacts to make training data more robust [**1**]. Such artifacts may be removed with averaging in the temporal domain.

Each BCI protocol can be improved. For the motor imagery protocol, the cursor could be made to oscillate and "jump" less. Some latency always exists, due to the time it takes a human mind to notice a change on screen and respond. The window size of 500 ms was designed to allow a subject time to notice a change and perform corrections, if necessary. A spatial filter was already employed in this protocol to minimize the contribution of non-motor cortex electrode channels. Despite this, motor and ocular artifacts could still interfere. The eyes of a subject tracked the cursor as it travelled across the screen. Eye-tracking could result in ocular activity [**1**]. Also, some subjects had difficulty in thinking about motor imagery. Subjects required practice to think of a particular motor skill without performing it. Therefore, the first two sessions of the motor imagery protocol are considered practice. Automatic artifact and noise rejection may improve user control for both BCI protocols, such as in [**9**] [**39**].

In the case of the P300 speller protocol, eliminating the cause of the latency may also improve performance. With less delay, a shorter sliding window may become more feasible. Another change may be to use a faster stimulus duration and flash rate in the P300 protocol. The time that each row and column is required to flash would be reduced. The resulting changes could increase in the amount of characters per minute. To increase the information transfer rate, the number of epochs to average could also be reduced. Reducing the number of trials could also make the system more susceptible to artifacts. With a lower number of averaged trials, the chance of artifacts in affecting the results becomes greater. Such occurrences could interfere with both calibration and use of the P300 system. Since averaging trials acts as a form of filtering, reducing the number of trials could introduce more artifacts into the signal [**1**].

Other changes that could be implemented include different sensory distractions (e. g. visual or different auditory ones). Subjects report that the sounds used for distraction repeated and become predictable, allowing them to anticipate and tune out the sounds. While visual distractions were removed from this study, similar distractions may be incorporated into newer protocols. New BCI protocols may also be employed, as well as new styles of memory and focus tests. While small in sample size, this study leaves open several possibilities for follow-up research.

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APPENDIX A: COMPLETE RESULTS

Table 1: Complete Verbal Learning Task and N Back Test Results

Accuracy		Verbal Learning Task			N Back Test		
Subject	Group	2 Min	20 Min	24 Hour	1 Back	2 Back	3 Back
1	Meditation	0.8	0.7	0.8	1	1	1
2	Meditation	1	0.6	0.7	1	0.925	0.9
3	Meditation	1	1	0.7	1	0.95	0.85
4	Control	1	0.8	0.7	1	0.9	0.7
5	Meditation	0.8	0.9	0.8	1	0.925	0.85
6	Control	0.9	0.9	0.7	0.975	1	0.825
7	Meditation	1	0.8	0.7	1	0.975	1
8	Control	0.9	1	0.7	1	0.725	0.65
9	Control	0.9	0.7	0.6	0.975	0.9	0.7
10	Meditation	1	0.9	0.8	0.975	1	1
11	Control	0.9	0.8	0.9	1	0.975	0.975
12	Control	0.9	0.8	0.7	1	1	0.9
13	Control	1	0.6	0.7	0.9	0.775	0.65
14	Meditation	1	0.8	0.8	1	0.975	0.9
15	Meditation	1	0.9	0.7	1	1	0.925
16	Control	1	0.9	0.7	1	0.98	0.925
17	Control	0.8	0.7	0.7	1	1	0.875
18	Control	0.8	0.8	0.6	1	0.95	0.925
19	Meditation	0.9	0.6	0.5	1	1	0.95
20	Meditation	0.8	1	0.5	1	0.875	0.7

Table 2: Complete Motor Imagery Results

Table 2-A: Motor Imagery BCI: No Distraction

Accuracy										
Subject	Group	1	2	3	4	5	6	7	8	9	10
1	Meditation	0.44	0.44	0.55	0.33	0.5	0.44	0.61	0.66	0.61	0.5
2	Meditation	0.5	0.5	0.5	0.44	0.44	0.5	0.5	0.5	0.33	0.55
3	Meditation	0.88	0.61	0.55	0.66	0.83	0.94	0.61	0.77	0.61	0.77
4	Control	0.44	0.44	0.61	0.66	0.44	0.44	0.44	0.5	0.5	0.44
5	Meditation	0.66	0.55	0.61	0.44	0.55	0.55	0.5	0.61	0.5	0.44
6	Control	1	1	1	1	0.83	0.94	1	1	1	1
7	Meditation	0.77	0.66	0.72	0.5	0.72	0.72	0.72	0.83	0.55	0.66
8	Control	0.61	0.5	0.66	0.83	0.61	0.66	0.38	0.66	0.61	0.66
9	Control	0.55	0.72	0.55	0.55	0.55	0.66	0.5	0.5	0.72	0.5
10	Meditation	1	1	1	1	1	1	1	1	1	1
11	Control	0.72	0.61	0.55	0.55	0.5	0.77	0.27	0.66	0.55	0.55
12	Control	0.44	0.44	0.55	0.33	0.5	0.44	0.61	0.66	0.61	0.5
13	Control	0.27	0.33	0.66	0.44	0.5	0.44	0.55	0.38	0.55	0.66
14	Meditation	1	1	1	1	0.94	0.94	1	1	1	1
15	Meditation	0.66	0.61	0.66	0.61	0.55	0.55	0.55	0.61	0.44	0.44
16	Control	0.5	0.5	0.72	0.66	0.72	0.61	0.66	0.44	0.55	0.27
17	Control	0.5	0.66	0.66	0.66	0.55	0.72	0.72	0.38	0.61	0.33
18	Control	0.33	0.5	0.38	0.66	0.33	0.66	0.55	0.5	0.55	0.55
19	Meditation	0.83	1	1	0.88	1	1	0.94	1	0.88	0.94
20	Meditation	0.61	0.38	0.55	0.38	0.61	0.61	0.44	0.5	0.55	0.61

Table 2-B: Motor Imagery BCI: Distraction

Accuracy										
Subject	Group	1	2	3	4	5	6	7	8	9	10
1	Meditation	0.66	0.61	0.66	0.5	0.44	0.44	0.5	0.55	0.44	0.5
2	Meditation	0.66	0.5	0.55	0.38	0.38	0.5	0.61	0.55	0.66	0.44
3	Meditation	0.61	0.77	0.94	0.94	0.77	0.83	0.77	0.94	0.77	0.77
4	Control	0.44	0.33	0.55	0.5	0.61	0.33	0.61	0.5	0.66	0.5
5	Meditation	0.66	0.5	0.61	0.55	0.61	0.72	0.5	0.61	0.5	0.44
6	Control	1	1	1	1	0.83	0.94	0.88	1	0.94	1
7	Meditation	0.94	0.88	1	1	0.94	1	1	1	1	1
8	Control	0.5	0.5	0.72	0.61	0.66	0.55	0.55	0.61	0.55	0.55
9	Control	0.38	0.72	0.66	0.5	0.61	0.66	0.38	0.66	0.55	0.44
10	Meditation	1	1	1	1	1	1	1	1	1	1
11	Control	0.61	0.55	0.61	0.61	0.5	0.66	0.55	0.5	0.44	0.5
12	Control	0.66	0.61	0.66	0.5	0.44	0.44	0.5	0.55	0.44	0.5
13	Control	0.5	0.5	0.61	0.5	0.72	0.72	0.44	0.44	0.33	0.61
14	Meditation	1	1	1	1	1	1	1	1	1	1
15	Meditation	0.5	0.33	0.38	0.33	0.61	0.72	0.66	0.83	0.66	0.55
16	Control	0.66	0.72	0.61	0.38	0.5	0.38	0.55	0.72	0.38	0.38
17	Control	0.66	0.72	0.72	0.72	0.66	0.72	0.66	0.66	0.66	0.72
18	Control	0.66	0.33	0.38	0.44	0.44	0.44	0.66	0.38	0.55	0.5
19	Meditation	0.88	1	0.83	1	0.94	1	0.88	0.94	1	0.94
20	Meditation	0.55	0.61	0.55	0.44	0.5	0.38	0.44	0.55	0.5	0.61

Table 3: Complete P300 Speller Results

Table 3-A

Accuracy		P300 Speller: No Distraction				P300 Speller: Distraction			
Subject	Group	1	2	3	4	1	2	3	4
1	Meditation	0.33	0.33	0.29	0.38	0.45	0.2	0.17	0.25
2	Meditation	0.25	0.75	0.75	0.35	0.71	0.41	0.45	0.71
3	Meditation	0.71	0.8	1	0.78	0.8	0.59	1	0
4	Control	0.58	0.5	0.75	0.86	1	0.83	0.5	0.41
5	Meditation	0.25	0.5	0.45	0.8	0.36	0.36	0.4	0.43
6	Control	1	1	1	0.78	1	1	0.83	0.78
7	Meditation	0.71	0.8	0.39	1	0.8	1	1	0.86
8	Control	0.32	0.07	0.2	0.08	0	0.14	0.08	0
9	Control	0.75	0.75	0.75	0.86	1	1	0.8	1
10	Meditation	0.08	0.08	0.08	0.14	0.25	0.08	0.14	0.08
11	Control	0.31	0.18	0.22	0.6	0.67	0.67	0.25	0.75
12	Control	0.2	0.3	0.42	1	0.8	0.8	0.56	0.71
13	Control	0.54	0.71	0.83	0.78	0.5	0.25	1	0.5
14	Meditation	1	0.8	0.7	0.5	1	0.71	0.65	0.83
15	Meditation	1	0.8	1	0.86	1	1	1	0.86
16	Control	0	0.17	0	0	0	0	0	0
17	Control	0	0.13	0	0	0	0	0	0
18	Control	1	1	0.4	1	0	0	0	0
19	Meditation	1	0.8	1	0.78	0.8	0.71	0.83	0.86
20	Meditation	0.8	0.8	0.83	0.86	0.8	0.8	0.83	0.78

Table 3-B

ITR (bit/min)		P300 Speller: No Distraction				P300 Speller: Distraction			
Subject	Group	1	2	3	4	1	2	3	4
1	Meditation	2.18	2.18	1.76	2.75	3.62	0.92	0.68	1.36
2	Meditation	1.36	8.2	8.2	2.4	7.5	3.11	3.62	7.5
3	Meditation	7.5	9.13	11.34	8.75	9.13	5.57	11.34	0
4	Control	5.42	4.28	8.2	10.31	11.34	9.71	4.28	3.11
5	Meditation	1.36	4.28	3.62	9.13	2.52	2.52	2.99	3.36
6	Control	11.34	11.34	11.34	8.75	11.34	11.34	9.71	8.75
7	Meditation	7.5	9.13	2.87	11.34	9.13	11.34	11.34	10.31
8	Control	2.07	0.09	0.92	0.13	0	0.47	0.13	0
9	Control	8.2	8.2	8.2	10.31	11.34	11.34	9.13	11.34
10	Meditation	0.13	0.13	0.13	0.47	1.36	0.13	0.47	0.13
11	Control	1.97	0.76	1.09	5.73	6.83	6.83	1.36	8.2
12	Control	0.92	1.86	3.24	11.34	9.13	9.13	5.13	7.5
13	Control	4.84	7.5	9.71	8.75	4.28	1.36	11.34	4.28
14	Meditation	11.34	9.13	7.33	4.28	11.34	7.5	6.51	9.71
15	Meditation	11.34	9.13	11.34	10.31	11.34	11.34	11.34	10.31
16	Control	0	0.68	0	0	0	0	0	0
17	Control	0	0.4	0	0	0	0	0	0
18	Control	11.34	11.34	2.99	11.34	0	0	0	0
19	Meditation	11.34	9.13	11.34	8.75	9.13	7.5	9.71	10.31
20	Meditation	9.13	9.13	9.71	10.31	9.13	9.13	9.71	8.75

ANOVA Tables

Table1-A: VLT Between-Subjects

Tests of Between-Subjects Effects

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	39.366	1	39.366	2977.261	.000
Group	.003	1	.003	.202	.659
Error	.238	18	.013		

Table 1-B: VLT Within-Subjects

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
vlt	Sphericity Assumed	.484	2	.242	22.454	.000
	Greenhouse-Geisser	.484	1.775	.273	22.454	.000
	Huynh-Feldt	.484	2.000	.242	22.454	.000
	Lower-bound	.484	1.000	.484	22.454	.000
vlt * Group	Sphericity Assumed	.001	2	.001	.062	.940
	Greenhouse-Geisser	.001	1.775	.001	.062	.923
	Huynh-Feldt	.001	2.000	.001	.062	.940
	Lower-bound	.001	1.000	.001	.062	.806
Error(vlt)	Sphericity Assumed	.388	36	.011		
	Greenhouse-Geisser	.388	31.957	.012		
	Huynh-Feldt	.388	36.000	.011		
	Lower-bound	.388	18.000	.022		

Table 2-A: N Back Between-Subjects

Tests of Between-Subjects Effects

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	51.996	1	51.996	4416.712	.000
Group	.037	1	.037	3.164	.092
Error	.212	18	.012		

Table 2-B: N Back Within-Subjects

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
nb	Sphericity Assumed	.176	2	.088	26.363	.000
	Greenhouse-Geisser	.176	1.424	.123	26.363	.000
	Huynh-Feldt	.176	1.598	.110	26.363	.000
	Lower-bound	.176	1.000	.176	26.363	.000
nb * Group	Sphericity Assumed	.017	2	.009	2.623	.086
	Greenhouse-Geisser	.017	1.424	.012	2.623	.106
	Huynh-Feldt	.017	1.598	.011	2.623	.100
	Lower-bound	.017	1.000	.017	2.623	.123
Error(nb)	Sphericity Assumed	.120	36	.003		
	Greenhouse-Geisser	.120	25.633	.005		
	Huynh-Feldt	.120	28.756	.004		
	Lower-bound	.120	18.000	.007		

Table 3-A: Motor Imagery BCI Between-Subjects

Tests of Between-Subjects Effects

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	17.113	1	17.113	266.330	.000	.937
Group	.169	1	.169	2.628	.122	.127
Error	1.157	18	.064			

Table 3-B: Motor Imagery BCI Within-Subjects

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F
mu	Sphericity Assumed	.006	1	.006	2.414
	Greenhouse-Geisser	.006	1.000	.006	2.414
	Huynh-Feldt	.006	1.000	.006	2.414
	Lower-bound	.006	1.000	.006	2.414
mu * Group	Sphericity Assumed	.004	1	.004	1.617
	Greenhouse-Geisser	.004	1.000	.004	1.617
	Huynh-Feldt	.004	1.000	.004	1.617
	Lower-bound	.004	1.000	.004	1.617
Error(mu)	Sphericity Assumed	.048	18	.003	
	Greenhouse-Geisser	.048	18.000	.003	
	Huynh-Feldt	.048	18.000	.003	
	Lower-bound	.048	18.000	.003	

Table 4-A: P300 BCI Between-Subjects

Tests of Between-Subjects Effects

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	12.199	1	12.199	66.872	.000
Group	.249	1	.249	1.364	.258
Error	3.284	18	.182		

Table 4-B: P300 BCI Within-Subjects

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
p3	Sphericity Assumed	.012	1	.012	.433	.519
	Greenhouse-Geisser	.012	1.000	.012	.433	.519
	Huynh-Feldt	.012	1.000	.012	.433	.519
	Lower-bound	.012	1.000	.012	.433	.519
p3 * Group	Sphericity Assumed	.004	1	.004	.151	.703
	Greenhouse-Geisser	.004	1.000	.004	.151	.703
	Huynh-Feldt	.004	1.000	.004	.151	.703
	Lower-bound	.004	1.000	.004	.151	.703
Error(p3)	Sphericity Assumed	.502	18	.028		
	Greenhouse-Geisser	.502	18.000	.028		
	Huynh-Feldt	.502	18.000	.028		
	Lower-bound	.502	18.000	.028		

APPENDIX B: RELEVANT FORMS

Rowan University
Electrical and Computer Engineering

Consent to Take Part

In a Research Study

1. Subject Name _____

2. Title of Research: **The Effects of Mental Training on BCI Performance with Distractions**

3. Investigator's Name: **Robi Polikar, Ph.D.; Bonnie Angelone, Ph.D; John LaRocco**

4. Consenting for the Research Study: This is an important document. If you sign it, you will be authorizing Rowan University and its researchers to perform research studies on you. You should take your time and read it carefully. You can also take a copy of this consent form to discuss it with members of your family, your physician, your attorney, or any one else you would like to consult with before you sign it. Do not sign this document unless you fully agree to participate in this study.

YOUR RIGHT TO PRIVACY AND CONFIDENTIALITY. We will collect personal information from you, which will be kept confidential. Very specific information on your right to privacy and the confidentiality of the use and disclosure of your personal health information can be found at the end of this consent form. We need your authorization to use and disclose the health information

that we may collect about you during this research study. To be in this research study you must read and sign the authorization at the end of this consent form.

5. Purpose of Research:

You are being asked to participate in a research study. The purpose of this study is to investigate brain activity and how brain responses vary when people follow a certain experimental protocol (described in detail next). Our short term goal is 1) to understand whether there is a link between certain cognitive / behavioral tasks and the responses in the EEG waves of the brain of normal subjects while working on those tasks; and 2) if such a link exists, whether it is stronger in persons who are following mental relaxation techniques, such that they are better able to follow protocol tasks in the presence of distractions. Our long term goal – not likely to be achieved in this immediate study – is to design effective brain-machine interface system that will i) allow people to use their thoughts to control mechanical devices, which would have a great impact in improving the quality of life of those with certain disabilities (such as Amyotrophic Lateral Sclerosis (ALS – aka, Lou Gehrig Disease)) that prevent them from using their extremities. ii) optimize our ability to learn; and iii) provide a mechanism to train people who are involved in high risk / high stress job environments.

We will be using electroencephalography (or EEG), which is a very well established technique for measuring the electrical output of the brain or its activity. EEG only measures the bioelectric energy generated by your brain's functioning; no external electrical activity will be applied to you.

About 15-20 people will participate in this phase of the study. You qualify for this study because – based on your acknowledgment - you are a physically healthy adult between the ages of 18 and 55, your eyesight is correctible to 20/20, you have no hearing loss, you are fluent in English, and you are willing and able to participate in several (see below) 30-90 minute sessions of EEG recording.

6. Procedures And Duration:

You understand that all of the following things that will be done to you are experimental, and that they are not designed to diagnose, treat or cure any disease.

If you agree to take part in this study, you will be asked to participate in one or more of the following protocols. We will typically ask you to perform no more than two protocols in any one sitting.

In each of the following protocols, you will be exposed to random distractions. These distractions may include the following:

- Audio stimuli: hearing unrelated sounds from a speaker;
- Visual stimuli: additional task-unrelated images on the corners of the monitor
- Tactile stimuli: gentle touches / bumps.

The nature, frequency and timing of these distracters will be random and unknown to you.

In all protocols, there will be a training and evaluation period. The training periods will be used to collect "training data" which will help us determine the appropriate predictors from your EEG for the given BCI task, and allow you to learn how to control your thoughts for the given BCI task. No distracters will be given during this period, that is, distracter stimuli will only be given during the evaluation period.

Training period may require several visits to the lab. The number of such visits may vary from person to person, so we do not know ahead of time how many times we will request your present. At a minimum, we anticipate at least three visits. You may decide to discontinue at any time.

Protocol 1. Focus on randomly flashing letters / numbers / characters / images on a matrix for virtual control of a multi-control device (such as a keyboard). For example, for the virtual keyboard, you will see a matrix of letters / numbers randomly flashing, and you will focus on the character you wish to spell (e.g. by counting each time that character flashes), one character at a time. The data collection section of this protocol will last about 30-40 minutes per sitting, and may be repeated several times to learn the correct associations with your EEG signals and the desired characters to be spelled. The data collection section of this protocol will last about 20 minutes.

Protocol 2. Try to remember up to 4 running letters in your memory, and respond by pressing a button when certain letter pairings occur. Running letters mean that you will try to keep in your mind the last 0, 1, 2, 3 or 4 letters of a sequence of letters that is continuously presented to you on a computer monitor. The data collection section of this protocol will last about 30-40 minutes. In the easiest form of this experiment, you will be asked to press a button every time a certain letter appears on the monitor (e.g., the letter "X") This is called 0-back. In the hardest part of this protocol, you will be asked to press a button every time a third letter repeats (e.g., in …T A K Z A…you will be expected to press a button after the "A" since the third letter after an "A" is also an "A"). This is called 3-back. Similarly, there will be 1-back and 2-back sessions. The data collection section of this protocol will last about 15-20 minutes.

Protocol 3. Move or think about moving an object in response to a series of external stimuli. For example, you may be asked to think about moving your left arm every time you see a left arrow, and think about moving your right arm every time you see a right arrow on a computer monitor. The data collection section of this protocol will probably last about 20-30 minutes.

Protocol 4 Look at a series of lights that are blinking / flashing at different rates (frequencies), and focus on the one that is encoded for a particular movement or task. For example, you may be looking at for lights flashing at four different frequencies (e.g., 8, 10, 12, and 14 Hz), each meaning a different task, e.g., moving a pointer / joystick left, right, up or down. Then, to move left, for example, you would focus on the light that is flashing at 8 Hz. The data collection section of this protocol will last about 15-20 minutes.

Protocol 5. Learn a number of word pairs which will be presented to you on a computer screen. The learning task will typically last about 30 minutes. After 30 minutes, and then again after 24 hours, we will ask you to return and demonstrate how many word pairs you can recall. You will be given one of the words from the pair, and asked to provide the paired word that you studied. If the word is a new one that you have not seen, you will say "new." If you remember that you have seen the word, but cannot remember the pair, you will say "pass." All verbal responses will be audio-taped for data synchronization and confirmation. After the verbal response, you will press one of four keys on a response pad based on your confidence in this judgment, i.e, "sure old", "think old", "think new", or "sure new".

We will measure your EEG signals while you are performing these tasks. Specifically, we will start with prerecording preparation where we will place electrodes on your head (many of which will be through an electrode cap). The electrodes will make contact with your skin through a conducting gel. While the electrode cap will fit your head comfortably like a hat, some electrodes will be secured to their location using a medical adhesive tape (not too dissimilar to a scotch tape, except designed for such medical use).The pre-recording preparation (placement of electrodes) typically takes about 20-30 minutes. We may first collect background data, for about 10 -15 minutes, during which you will be simply resting with your eyes open (5-7 minutes) and eyes closed (5-7 minutes). You will also be able to take regular breaks every 3 to 10 minutes depending on the task.

Again, note that we may ask you to participate in all or only a few of these protocols, and you are free to participate in as many or as few of these protocols you are asked to participate. We will also ask you to repeat certain protocols, in particular protocols 1, 3 and 4. You are free to participate only as many times as you wish.

7. Risks And Discomforts/Constraints:

No invasive operation is needed to measure brain activity. The only potential discomfort – which is very rare, is possibly from skin irritation due to the medical grade gel, or the medical grade adhesive and salt in the adhesive paste used to attach the EEG electrodes. If you have ever had significant irritation or an allergic reaction to a medical adhesive such as skin tape, please inform the investigator. Some individuals with very sensitive skin may experience a slight reddening or sensitization of their skin from the salt in the adhesive paste used to attach the EEG electrodes. This is the same as being exposed to salt water for 30 minutes to an hour. No physical discomfort

should be associated with the procedure. However, if you feel uncomfortable in any way, you should inform the investigator, and the study will be stopped immediately.

You may also wish to wash your hair (with shampoo) soon after the removal of the electrode cap, primarily for cosmetic reasons. If you wish, the investigators will schedule you at a time (for example evenings) suitable for you to go home for a shower following the procedure. While extremely rare, you may inform us at any time should the electrode cap becomes uncomfortable to wear, at which time we will stop data collection and remove the cap.

9. Unforeseen Risks:

All research carries some rare, unanticipated or unknown risks. If unforeseen risks are noted, the study will be stopped and the Institutional Review Board, which has approved this study, will immediately be notified.

10. Benefits:

There are unlikely to be any direct benefits to you from participating in this study.

11. Alternative Procedures/Treatment:

Since you are volunteering to participate in this study, you may simply choose not to participate in the study. You may choose to stop at any time during the study, with no consequence to you.

13. Reasons for Removal from Study:

You may be required to stop the study before the end for any of the following reasons:

a) Change in your medical or physical condition
b) If all or part of the study is discontinued for any reason; or
c) Other reasons, including new information available to the investigator or harmful unforeseen reactions experienced by the subject or other subjects in this study.

14. Voluntary Participation:

Participation in this study is entirely voluntary, and you can refuse to be in the study or stop at any time for any reason. Refusal to participate in this study and/or choosing to terminate your participation will have no penalty or loss of benefits to which you are otherwise eligible. If you are a student who signed up to be involved in the related clinic project as part of your course work, you may revoke your consent and choose not to have your EEG acquired at any time. Your course grade will be determined solely on your performance on the data analysis part, and refusing to participate in having your EEG collected will have no negative impact on your grade.

15. Stipend/Reimbursement:

There will be no stipend or honorarium paid for participating in this study.

16. Responsibility for Cost:

All data acquisition cost (for example, the cost of materials and supplies) for participation in this study will be assumed by College of Engineering of Rowan University. If you are a non-Rowan student / participant, and you have traveled to come to Rowan University for this study, your travel costs will be reimbursed up to $20.

17. In Case Of Injury or for Questions:

You have been told that if you have any questions or believe that you have been injured in any way by being in this research project, you should contact Dr. Robi Polikar at telephone number (856) 256-5372 or by e-mail at polikar@rowan.edu. However, you understand and agree that neither the investigator nor Rowan University will make payment for injury, illness, or any other loss resulting from your being in this research project.

If you have any questions about your rights as a research subject, you may contact the Associate Provost for Research at:

Rowan University Institutional Review Board for the Protection of Human Subjects
Office of Research
201 Mullica Hill Road
Glassboro, NJ 08028-1701
Tel: 856-256-5150

18. Use of Recording Devices

If you agree, the investigator will photograph and/or video tape you during the preparation and / or data collection. This information may be used in several ways, such as to monitor your level of comfort, focus, attention during the recording, to demonstrate to others how the entire experimental procedure is conducted, to present at scientific conferences, or even for promotional purposes to recruit future students / participants to this study. You may disagree to the use of recording devices, but still participate in the study, simply by indicating your choice at the end of this document.

The only exception to this is the audio recordings of your responses in the word pairing test. As per the protocol, audio recordings of your responses in this experiment are required. If you do not wish your voice to be recorded, you may simply decline to participate in the word pairing task all together, and perform other protocols.

19. CONFIDENTIALITY AND PRIVACY:

This section gives more specific information about the privacy and confidentiality of your health information. It explains what health information about you will be collected during this research study and who may use, give out and receive your health information. It also describes your right to inspect your medical records and how you can revoke this authorization after you sign it.

By signing this form, you agree that your health information may be used and disclosed during this research study. We will only collect information that is needed for the research study. Your health information will only be used and given out as explained in this consent form or as permitted by law.

In any publication or presentation of research results, your identity will be kept confidential.

A. Information that will be collected

The following personal health information about you will be collected and used during the research study and may be given out to others:

1. *Your name and date of birth (to determine that you an adult between the ages of 18 and 55;*
2. *Are you left handed? (to control for a potential confound factor in data analysis)*
3. *Personal medical history (participants giving a yes answer to any of the following questions will not be included in this study):*
   a. Do you have vision problems that cannot be corrected to 20/20 vision?

   b. Do you have difficulty in understanding, speaking or comprehending the English language?

   d. Are you diagnosed with any hearing loss or do you have any hearing difficulty?

   e. Do you have any history of seizure, head injury or any other neurological disorder including stroke?

   f. Have you been diagnosed with any clinical psychological / mental disorders, also known as DSM-IV Axis I disorders?

   g. Have you been diagnosed with and/or admitted to a treatment program for drug / alcohol abuse?

   h. Do you use any medication that may affect your neurological function?

   j. Are you pregnant (for women)?

4. Is there any additional information you wish to provide, or you think we should know, during this research study?

B. Who will see and use your (health) information within Rowan University

The research study investigator and other authorized individuals involved in the research study at Rowan University will see this information and may give out your health information during the research study. These include the research investigator and the research staff, the institutional review board and their staff, legal counsel, research office and compliance staff, officers of the organization and other people who need to see the information in order to conduct the research study or make sure it is being done properly.

C. Who else may see and use your health information

Other persons and organizations outside of Rowan University may see and use your health information during this research study. These include:

- **Governmental entities that have the right to see or review your health information, such as the Office of Human Research Protections and the Food and Drug Administration**

- **Research information only (e.g., your accuracy in responding to any of the tasks), but not identifying information (such as name, address, telephone number, date of birth, social security number; or personal medical history) may be shared with sponsoring agencies and/or scientific communities (via conferences, papers, etc.). Such research data will be identified only by a random code (such as Subject A, Subject B).**

D. **Why your health information will be used and given out**

Your health information will be used and given out to carry out the research study and to evaluate the results of the study. Your information may also be used to meet the reporting requirements of governmental agencies.

E. If you do not want to give authorization to use your health information

You do not have to give your authorization to use or give out your health information. However, if you do not give authorization, you cannot participate in this research study.

F. How to cancel your authorization

At any time you may cancel your authorization to allow your health information to be used or given out by sending a written notice to Rowan University Institutional Review Board for the Protection of Human Subjects, Office of Research, 201 Mullica Hill Road

Glassboro, NJ 08028-1701. If you leave this research study, no new health information about you will be gathered after you leave. However, information gathered before that date may be used or given out if it is needed for the research study or any follow-up.

G. When your authorization ends

Your authorization to use and give out health information will continue until you withdraw or cancel your authorization. After the research study is finished, your health information will be maintained in a research database. Rowan University shall not re-use or re-disclose the health information in this database for other purposes unless you give written authorization to do so. However, the Rowan University Institutional Review Board may permit other researchers to see and use your health information under adequate privacy safeguards.

H. Your right to inspect your medical and research records

You have the right to look at your medical records at any time during this research study. However, the investigator does not have to release research information to you if it is not part of your medical record.

19. Other Considerations:

If new information becomes known that will affect you or might change your decision to be in this study, you will be informed by the investigator. If you have any questions at any time about this study or your rights as a research subject, you may contact Dr. Polikar and the Office of Research at (856) 256-5150.

20. Consent:

- **I agree to participate in this study entitled " Electroencephalogram acquisition and analysis for brain-machine interface" which is being conducted by Dr. Robi Polikar of the Electrical and Computer Engineering, College of Engineering of Rowan University**
- **I have been informed of the purpose, goals and short and long term benefits of this study.**
- **I have had the study explained to me. I understand that I will be expected to follow the experimental protocols summarized in this document, while my EEG is being acquired. I understand that I can participate in as many or as few protocols I wish, each of which should take about 2 hours (including pre-recording preparation) total, with 30-90 minutes of EEG recording.**
- **The potential risks / discomforts associated with this study have been explained to me. I understand that to the best knowledge of the investigator, there are no physical or**

psychological risks involved in this study – apart from those described in this consent form, and that I am free to withdraw my participation at any time without penalty.

- **I have had all of my questions answered.**
- **I have carefully read this consent form, have initialed each page, and have received a signed copy.**
- **I understand that any personally identifiable information gathered will be confidential. I agree that any information obtained from this study may be used in any way thought best for publication or education provided that I am in no way identified and my name is not used. I authorize the use and disclosure of my personal health information as explained in this consent form.**
- **I understand that my participation does not imply employment with the state of New Jersey, Rowan University, the principal investigator, or any other project facilitator.**
- **I give consent willingly and voluntarily.**

_____ _____

Subject **Date**

- I also give consent to be photographed and/or videotaped, which may later be used as described in this document (lack of subject signature below will indicate that you decline to consent to be photographed / videotaped).

_____ _____

Subject

Date

_____ _____

Investigator or Individual Obtaining this Consent **Date**

List of Individuals Authorized to Obtain Consent and Conduct Experiments

Name	**Title**	**Day Phone #**	**E-Mail**
Robi Polikar, Ph.D.	Principal Investigator	(856) 256-5372	polikar@rowan.edu
Bonnie Angeleno, Ph.D.	Co-investigator	(856) 256-3753	angelone@rowan.edu
John LaRocco	Graduate Research Asst.	(856) 256-5351	larocc25@students.rowan.edu
James Etheridge	Graduate Research Asst.	(856) 256-5351	ethrid60@students.rowan.edu

Participant Information

Name:

Date of Birth:

Sex:

Year in school:

Major:

Are you left handed?	Yes	No
Do you have normal vision (possibly corrected-to-normal vision) (circle one) ?	Yes	No
Do you have difficulty in understanding, speaking or comprehending the English language?	Yes	No
Are you diagnosed with any hearing loss or do you have any hearing difficulty?	Yes	No
Do you have any history of seizure, head injury or any other neurological disorder including stroke?	Yes	No
Have you been diagnosed with any clinical psychological / mental disorders, also known as DSM-IV Axis I disorders?	Yes Yes	No No
Have you been diagnosed with and/or admitted to a treatment program for drug / alcohol abuse?	Yes	No
Do you use any medication that may affect your neurological function?	Yes	No
Are you pregnant (for women)?	Yes	No
Have you had experience with meditation before (circle one)?	Yes	No

If Yes, how long have you been first practicing meditation?

If Yes, what type of actions or relaxation techniques do you prefer?

If Yes, how often do you practice meditation (please check one)?

___Never ___Once A Year ___Once a Month ___Once a Week ___Daily

Is there any additional information you wish to provide, or you think we should know, during this research study (you may use the back of this for your answers?