

A 3D Printed, Non-Invasive Brain Computer Interface Prosthetic Hand

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# Abstract

Millions of people across the world are living with a form of upper limb disability. Studies have shown that the most prominent causes of this disability are stroke, spinal cord injury, and multiple sclerosis (MS) [1]. Impairment of the upper limbs can be caused by a breakdown in the neural signalling pathway, between the motor cortex and the skeletal muscles in the affected limb. In many cases, the function of the cortex remains sufficiently intact for the neural signalling patterns to be intercepted, decoded, and an appropriate motor action executed by an assistive device. This is the role of Brain Computer Interface (BCI) Neuroprosthesis. Such devices have the potential to make a dramatic positive impact on the lives of millions of people living with paralysis or reduced motor function, restoring ability and independence. This project will explore the design and development of a 1 Degree of Freedom (DOF) prosthetic hand, controlled by the real-time, online classification of electroencephalography (EEG) signals obtained from the scalp of a healthy 22-year-old male. To achieve this outcome, hardware and software design and implementation, fused deposition manufacturing (FDM), simulation, data-acquisition, machine learning, control theory, and signal processing was conducted. This report will provide the biological background behind voluntary movement in the context of a BCI system, a summary of non-invasive BCI systems published in literature, a simulation of published feature extraction and classification techniques, an outline of the designed system, and testing methodologies. It was found that a Linear SVM outperforms the other classifiers considered in this report when comparing the systems on the same EEG dataset (74.59% classification accuracy). Due to its sophisticated dimensionality reduction characteristics, features extracted using a Discrete Cosine Transform (DCT) approach result in reduced classification time for equivalent classification accuracy when compared to the current state-of-the-art Short Time Fourier Transform (STFT) approach. The application of the DCT to EEG classification is a novel approach, and could represent a significant decrease in classification time for online BCIs. The proposed system includes a wireless EEG data acquisition system, built around the Texas Instruments ADS1299 and ATmega328P, a Classification and Control board, built on the ST Electronics STM32F407, and a carbon fibre 3D printed InMoov robotic hand, designed by Gael Langevin. Several tests of the system are proposed in this report, which outline the path forward to progress from system designs to a functional, non-invasive BCI neuroprosthetic.

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# Nomenclature

|  |  |
| --- | --- |
| AAR | Adaptive Autoregressive |
| ADC | Analog to Digital Converter |
| AFE | Analog Front End |
| Ag | Silver |
| AgCl | Silver chloride |
| AP | Action Potential |
| AR | Autoregressive |
| BCI | Brain Computer Interface |
| CONFIG1 | ADS1299 configuration register number 1 |
| CONFIG3 | ADS1299 configuration register number 3 |
| DC | Direct Current |
| DCT | Discrete Cosine Transform |
| DOF | Degree(s) of Freedom |
| DRDY | ADS1299 Data Ready Pin |
| DWT | Discrete Wavelet Transform |
| ECoG | Electrocorticography |
| EEG | Electroencephalography |
| EMI | Electromagnetic Interference |
| ERD | Event Related Desynchronisation |
| ERS | Event Related Synchronisation |
| FDM | Fused Deposition Modelling |
| FIFO | First In, First Out |
| FRI | Florida Research Instruments |
| FTDI | Future Technology Devices International |
| GPIO | General Purpose Input Output (pin) |
| IDE | Integrated Development Environment |
| IMDCT | Inverse Modified Discrete Cosine Transform |
| K | Potassium |
| kNN | *k*-Nearest Neighbours |
| LDA | Linear Discriminant Analysis |
| LSTM | Long Short-Term Memory (classifier) |
| M1 | Motor Cortex |
| MDCT | Modified DCT |
| MISC1 | ADS1299 reference electrode configuration register |
| MIT | Massachusetts Institute of Technology |
| MOSI | Master Out Slave In (SPI communication) |
| MS | Multiple Sclerosis |
| MSB | Most Significant Bit |
| Na | Sodium |
| PC | Personal Computer |
| PCB | Printed Circuit Board |
| PWM | Pulse Width Modulation |
| QDA | Quadratic Discriminant Analysis |
| RBF | Radial Basis Function |
| RC | Resistor-Capacitor |
| RDATA | ADS1299 command to retrieve data |
| RESET | Command to reset ADS1299 |
| SCLK | Serial Clock Pin |
| SDATAC | Command to stop ADS1299 continuous data conversion |
| SPI | Serial Peripheral Interface |
| SSVEP | Steady State Visual Evoked Potentials |
| START | ADS1299 command to start conversion |
| STATUS | ADS1299 Communication Header Packet |
| STFT | Short Time Fourier Transform |
| SVM | Support Vector Machine |
| TI | Texas Instruments |
| UART | Universal Asynchronous Receiver/Transmitter |
| USB | Universal Serial Bus |
| Vpp | Volts (peak to peak) |
|  | A Normal distribution function |
|  | Quantisation Coefficients for DCT Analysis |
|  | Forgetting Factor in AAR model |
|  | Error in the Least Squares criterion |
|  | Noise function in AAR model |
|  | Order of AAR model |
|  | Chip Select Pin (active low) |
|  | Number of bits per ADS1299 reading |
|  | Number of ADS1299 Channels |
|  | DCT Coefficients |
|  | Quantised DCT Coefficients |
|  | Period of ADS1299 Data Rate |
|  | Period of Serial Clock (SPI communication) |
|  | Time delay between sending bytes during a multi-byte command to ADS1299. |

# Introduction

Across the globe, millions of people are living with upper limb disability [2]. This disability may be caused by several factors, including amputation, spinal cord injury, paralysis, stroke, or degenerative disease [1, 3-5]. This disability reduces the independence and quality of life of the patient, resulting in increased levels of care and medical attention. In many cases, the cortical activity of people living with these conditions remains unaffected. Brain Computer Interface (BCI) technology aims to utilise the patterns of neuronal activity to decode the intent of the patient, then implement the intended outcome with the assistance of a computer [6]. Currently, research is being conducted at several leading universities across the globe to develop advanced BCI neuroprosthetic devices [7, 8]. These devices will use the patient’s neural signalling to control a robotic prosthetic, restoring their ability and independence. These devices will also reduce the financial impact on healthcare services presented by the care and rehabilitation of people with an upper limb disability. Most of the advanced neuroprosthesis being researched rely on implanted subcranial cortical electrode arrays [9]. This approach is called electrocorticography (ECoG), and offers a higher signal to noise ratio, and better spatial resolution than other approaches. However, a survey conducted in 2015 indicated that the high risk associated with the implantation procedure made this approach unattractive to people living with upper limb disability [10].

This project will assess the aptitude of electroencephalography (EEG), a non-invasive neural recording approach, as a BCI input modality. It is anticipated that through the application of several signal processing techniques, including the Short Time Fourier Transform (STFT) and Discrete Cosine Transform (DCT), the most advantageous approach can be devised. Similarly, by comparing several classification techniques including *k*-nearest neighbours (kNN), Support Vector Machines (SVM), and Adaptive Autoregressive techniques (AAR), the most superior classifier (most accurate per unit time) can be determined. Some publications have conducted a similar comparison [11-14], however these publications compared each approach on different datasets, acquired under different conditions. Therefore, conducting a comparison of feature extraction and classification techniques on the same dataset represents a novel contribution.

Once the most advantageous approach has been determined, it is anticipated that a system to implement this approach in an online BCI neuroprosthetics setup can be designed. To reduce artefacts (introduced from lead-sway, switching transients, etc.), a wireless EEG data acquisition system will be designed. Additionally, the classification and control hardware will be designed to fit within the spatial constraints of a 3D printed prosthetic forearm.

Through the development of a non-invasive online BCI neuroprosthetic device, an understanding of the advantages and disadvantages of EEG as a BCI input modality can be ascertained. It is hoped that the insights gained throughout the classification methodology assessment and the implementation of the system may guide future research in this area.

# Biological Background

The human brain is an incredible complex entanglement of various specialisations of cells. The modern field of neuroscience can be traced back to the 19th century, when Jean Legallois concluded that the medulla oblongata had a dominant role in respiration [15]. Since then, while unprecedented progression and understanding has occurred, there are still many neurological processes, such as memory and consciousness, with unknown mechanisms. Recently, advanced studies in the physical structure of the brain, connectomics, aims to increase humanity’s understanding by examining the connectedness of functional structures of the brain. Additionally, if the neural connections are known to a sufficient degree, whole regions of the brain may be computationally simulated [16]. This would provide a testbed for novel neuroactive medicines, or predictions of the impact of a stroke in a particular brain region.

## Neurons

The general term for the cells that make up the brain are neurons. A neuron consists of dendrites (inputs), a soma, an axon, and axon terminals (outputs) [17]. The neurons that make up the brain communicate through electrochemical signalling, called action potentials (APs). The cell membrane of the neuron sits at a resting potential of approximately -70 mV [18]. The membrane potential is set by the concentration of different ions inside the intracellular fluid of the soma. The intracellular fluid contains a higher concentration of potassium ions ([K+]) and a lower concentration of sodium ions ([Na2+]) than the intercellular fluid. The concentration gradient of the sodium ions is greater than that of the potassium ions, due to an increased permeability of the membrane to potassium [19].

Received excitatory APs from neighbouring neurons raises the membrane potential of the neuron incrementally, until a threshold potential is reached, when a series of events occur. Initially, voltage gated sodium channels open, allowing an influx of Na2+ ions from the intercellular fluid to enter the cell, depolarising it further. Once the membrane potential is slightly more positive than the intercellular fluid, voltage gated potassium channels open, allowing for K+ efflux from the cell body, and the voltage gated sodium channels close. This allows the cell to depolarise again. When the cell returns to its resting potential, the voltage gated potassium channels close [20].

APs initiate in the soma, then propagate along the axon to the axon terminals, where the neuron may synapse (connect) to a neighbouring neuron [21]. After passing through various cortical areas, the signal may synapse to a projection neuron, which will carry it down the spinal cord and into the peripheral nervous system.

## Cortical Areas for Voluntary Movement

The brain has been divided into defined cortical areas, each with a specific set of connections and functions. The cortical area responsible for voluntary motor control is the motor cortex (M1) [22], located in the precentral gyrus, and shown in Figure 1.

Figure 1 - A schematic diagram indicating the locations of cortical areas responsible for voluntary movement [23].

The M1 is present in the left and right hemispheres of the brain. Left side movements are lateralised to the right hemisphere M1, while right side movements are lateralised to the left hemisphere M1, thus the M1 possesses contralateral control [24].

The imagination or execution of a motor control command (e.g. right-hand grasp) will case an Event Related Desynchronisation (ERD) or an Event Related Synchronisation (ERS) [25]. During an ERD, neurons which were typically firing APs at a similar frequency will begin to fire APs at differing frequencies, resulting in a decrease in the spectral power of the old, synchronous frequency. Contrarily, during an ERS, neurons which were typically firing APs at different frequencies will begin to fire APs at a similar frequency, resulting in an increase in the spectral power at the new, synchronous frequency [26]. Many BCI systems classify motor intent by considering the change in spectral power characteristic to an ERD/ERS [27-29].

During the trial conducted by Burgess in [30], participants were presented with a series of photos of faces. Their EEG spectral density pre- and post-stimulus was compared to identify the incidence of a “seen” or “new” face. The key results relating to ERD/ERS is shown in Figure 2. Note that there is a significant reduction in spectral power at 10 Hz in the post-stimulus curve, characteristic of an ERD. Both curves were recorded at the Oz electrode site (on the centre line, above the occipital lobe) in the 10-20 international system.



Figure 2 - Comparison of pre- and post-stimulus action potential frequency at the Oz electrode, indicating an ERD [30].

## Electroencephalography (EEG)

EEG is a low-cost, non-invasive recording method to measure neural activity. It relies on the electrical currents generated by populations of thousands of neurons firing action potentials to conduct a small voltage signal to the cutaneous tissue of the scalp. The signals are detected using an array of electrodes.

Since EEG is measuring the activity of a general population of neurons, the spatial resolution of EEG is low. It is difficult to distinguish activity originating directly under the EEG electrode from activity emanating from a cortical region under an adjacent electrode [31]. However, EEG systems offer a high temporal resolution, limited only by the sampling rate of the data acquisition system [32]. This makes EEG neural recording methodologies attractive in a time-frequency Brain Computer Interface environment.

The electrodes commonly used to record the scalp potentials are classified as “wet” or “dry”. Wet electrodes require extensive scalp preparation, and the application of a conductive gel [33]. This made wet electrodes cumbersome, and slowed the testing process. Recent advances in dry electrodes have improved their signal acquisition properties to perform similarly to wet electrodes [34-36]. Dry electrodes do not require extensive preparation of the scalp, and can perform effectively through hair, due to the spiked nature of the electrode. Figure 3 compares the visual characteristics of wet and dry electrodes.

Figure 3 - (a) A gold cup "wet" electrode [37], and (b) a “dry” electrode [38].



(a)

(b)

The international standard EEG electrode locations follow the 10-20 system, presented in Figure 4. A standardised approach to electrode location ensures the same cortical areas are measured across trials and subjects. Additionally, this approach enables hardware to be manufactured to suit the standard, rather than follow proprietary location schemes. Wang et. al, identify the optimal locations for EEG electrodes to record motor imagery are C3, C4, and FCz on the 10-20 scheme, as these locations correspond to the right hand, left hand, and sensory motor area respectively.

Figure 4 - A diagram representing the 10-20 standard EEG electrode locations [39].

# Literature Review

To facilitate an online Brain Computer Interface control system, it is widely accepted that three main functional blocks are required. These blocks are presented in Figure 5.

Figure 5 - System block diagram indicating the basic functional blocks of a BCI system

Each of these blocks can consist of different approaches and procedures. A literature review, in conjunction with a MATLAB simulation, was conducted to predict the relative performance of each potential system. This enabled a reduction in the number of potential solutions, and the eventual derivation of an optimal system.

## Data Acquisition and Pre-processing

To analyse the neurological changes initiated by motor imagery processes, a method of effectively capturing the electrical signalling of the brain is required. This method should minimise the effect of noise from external sources. Then, since the device is a Brain Computer Interface, a method of digitising, communicating, and recording the results is necessary. Following this, some pre-processing may be necessary.

### Signal Recording Methods

There are several well documented means of recording neural activity from the human brain. At a high level, these can be divided into invasive and non-invasive methods. Invasive methods, such as electrocorticography (ECoG), offer some advantages over non-invasive methods. These methods exhibit reduced signal attenuation due to the sensors being placed under the parietal bones of the skull [40], improving the signal to noise ratio. They are also not susceptible to artefacts introduced from oculomotor or skeletal motor events. However, placement of these subdural electrodes poses significant risk, and is usually only implanted for clinical reasons in patients for epilepsy monitoring [41]. This risk is so significant, that a survey conducted by Engdahl et al. concluded that only 39% of participants indicated an interest in prosthesis controlled by (implanted) cortical interfaces, compared to 83% for myoelectric control [10]. Additionally, the scope of this report restricts the final system to be low-cost, which precludes an invasive recording method.

Scalp-based electroencephalography (EEG) is a common low-cost, portable recording method [42]. Using this approach, electrodes are placed on the scalp of the subject, which detect the ionic currents generated by the brain during an action potential [34]. These signals are extremely small, and are prone to radiated EMI from proximal sources. For decades, the accepted standard for electrodes were Ag/AgCl wet electrodes. These devices were passive, and required extensive preparation of the skin and electrode to ensure a low electrode-skin impedance. Usually this preparation is conducted by a trained specialist, took several minutes, and left a gel residue on the subject’s head [35]. Recently, however, new technology in the form of an active, dry electrode has enabled rapid acquisition of EEG signals, requiring practically no setup. These dry electrodes have been evaluated by multiple sources to perform to an equivalent standard as wet electrodes [34-36]. Such devices are attractive in this project, as they will enable rapid testing and development, at a low cost.

### Digitalisation Methods

Due to the signal’s susceptance to EMI, and to reduce the impact of aliasing introduced by time-domain sampling, most systems proposed in literature have included some form of lowpass filtering on the input stage of the analog to digital converter (ADC) [43, 44]. Application notes for some EEG analog front end (AFE) integrated circuits indicate that a single order passive RC lowpass filter is sufficient to mitigate the coupling of high frequency noise sources, and reduce the amplitude of high frequency content of the signal, in turn reducing the effect of aliasing [45]. This is an attractive solution, since these filters consume no power, enabling the data acquisition front end to be powered from a DC battery. Powering the device in such a manner reduces the likelihood of introducing conduction EMI into the signal from a rectified source [46].

Published literature appreciates that designing an AFE from scratch is a non-trivial task [47], and many papers suggest using an off the shelf component [48]. Several studies have selected the Texas Instruments (TI) ADS1299 chip to serve as the AFE when designing a BCI [47-52]. This chip is an attractive solution, due to its 24-bit resolution, high sample rate range (from 250 to 16k samples per second), high common-mode rejection ratio (-110 dB), low input referred noise (1 µVpp over a 70Hz bandwidth), and small, self-contained package [53]. The performance of this chip exceeds the performance of the AFE designed by Hu et al. in [47]. The chip interfaces to a microcontroller through an SPI interface. Additionally, the ADS1299 can be configured to use a single reference electrode, in a referred montage scenario, or establish differential signals when recording in a differential montage [54]. An evaluation board is available for this chip, however, TI has published a recommended schematic and PCB layout, which may serve as a valuable starting point from which a custom front end can be designed [45]. Thus, due to extensive prior works, and detailed supporting information, the TI ADS1299 AFE may be a viable solution to the EEG digitalisation problem.

## Feature Extraction

To reduce the computational intensity required to classify the EEG event, a feature extraction algorithm is applied to the acquired signal. Proposed algorithms include a Short Time Fourier Transform approach (STFT), an Adaptive Autoregressive Model (AAR), a Discrete Wavelet Transform (DWT), and a Discrete Cosine Transform (DCT) approach. It is noted that the articles cited use different testing data and methodologies, thus a valid absolute performance comparison cannot be made without evaluating these approaches against the same dataset. Additionally, the quoted performance of the feature extraction algorithm is dependent on the performance of the classification technique employed by the study, again reducing the validity of an absolute performance comparison.

### Adaptive Autoregressive Model (AAR)

An Adaptive Autoregressive Model (AAR) is a variation on an Autoregressive Model (AR), which allows the parameters of the model to adjust over time. This feature is beneficial when applied to an EEG signal, as the signal is non-stationary [55]. An AAR model of order is described by:

(1)

, and

(2)

Where is the n-th sample of the EEG observation, is the zero-mean-Gaussian noise with variance , and are the time-varying AR coefficients. Thus, a sample is predicted by the past samples, with new information introduced to the model through the innovation function , which in the above example is a normal distribution [56].

In some models, it is not beneficial to apply an equal weighting to all historical values. In this case, a “forgetting factor” is introduced, where:

(3)

which usually takes the form .

As proven by Haykin in [57], a recursive algorithm is applied to find the vector such as to minimise the sum of the error squares:

(4)

where is the vector of desired responses.

Applying the following variable changes:

(5)

enables the criterion presented in Equation (4) to be rewritten as the standard least squares criterion:

(6)

Thus, assuming a causal signal, the least squares solution can be obtained as:

(7)

where:

(8)

It can be shown through the matrix inversion formula, that:

(10)

(9)

can be written as:

(11)

Defining and

(12)

it can be shown that:

(13)

Thus, it is now possible to derive a time-update equation for :

(22)

(21)

(20)

(19)

(18)

(17)

(16)

(15)

(14)

where

Now all the required equations to form the recursive least squares algorithm have been produced, and are summarised as follows:

(26)

(25)

(24)

(23)

It is shown by Haykin that this recursive algorithm can be solved with relative computational ease, however the computational intensity increases with [57].

Such a model considers only time-domain parameters, thus utilising the high temporal resolution offered by EEG data acquisition systems at the peril of ignoring the prominent frequency-domain characteristics induced by ERPs. Low order models () are not computationally intensive, however accuracy increases with model order. Prior works indicate that AAR approaches may result in low accuracy, with Rodríguez-Bermúdez & García-Laencina reporting a 62.2% accuracy [58].

### Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a time-frequency approach, thus utilising both the temporal resolution of EEG signals, and the frequency characteristics of ERPs. This approach involves passing the signal through a multi-stage filter bank, consisting of highpass and lowpass filters. The highpass filtered signal produces the “detail coefficients” at that level of the filter bank, while the lowpass filtered signal produces the “estimate coefficients”. The lowpass filtered signal is then passed to the next level of the filter bank, as shown in Figure 6.

Since the frequency content of the signal has been bandlimited to one half of its original bandwidth, by Nyquist’s theorem, the signal can be subsampled by a factor of 2, reducing the number of samples at each step. In turn, this doubles the frequency resolution. Thus, DWT approaches offer high spectral resolution over the low frequency content. This characteristic is beneficial when extracting features from EEG data for motor imagery, since these signals occur in the low frequency spectrum, however a higher resolution will increase the computation time compared to analysing the STFT over a similar bandwidth.

When paired with a Long Short-Term Memory (LSTM) classifier, Jie Zhou et al. achieved an accuracy of 91.43% on the Graz 2003 Brain Computer Interface Competition III dataset [59]. Thus, the DWT method may be suitable for online motor imagery feature extraction.



Figure 6 - The filter bank representation of the DWT [60].

### Short Time Fourier Transform (STFT)

The Short Time Fourier Transform (STFT) approach is another time-frequency feature extraction method, again making use of the high temporal resolution offered by EEG signals and the identifiable frequency characteristics of ERPs. Under this approach, a sliding feature extraction window of defined length is passed over the EEG signal (in online analysis, this can be implemented using a FIFO buffer), and the discrete Fourier transform (DFT) of the signal in the window is taken. There are several windows to choose from, including:

1. Rectangular. This is the least computationally intensive window, however leads to increased sidelobes in the frequency domain which will need to be filtered.
2. Triangular. This window is slightly more computationally intensive, however the sidelobes will be somewhat compressed.
3. Hanning. This window is more computationally intensive, however offers the best compression of frequency domain sidelobes.

Huang et al. tested rectangular, triangular, Hamming, and Hanning windows when extracting features from Steady State Visual Evoked Potentials (SSVEP). Each of the windowed signals were passed to the same Linear Discriminant Analysis (LDA) classifier. It was found that if no highpass filter was applied, the triangular, Hamming, and Hanning windows performed equivalently (classification accuracy was within 0.5%), while the rectangular window did not perform as well. However, after a 4th order Butterworth highpass filter (cut-off frequency of 2 Hz) was applied to all the windowed signals, the rectangular window outperformed the rest of the windows. Thus, it is recommended by the authors of that paper that a rectangular window be used in conjunction with a 4th order highpass filter, for SSVEP analysis [61]. However, if a 4th order highpass filter is not applied, a triangular window is a computationally efficient, high-performance window function.

To circumvent the amplitude suppression introduced at the fringes of the window, the feature extraction window is “slid” over the length of the EEG signal. This means that each time domain sample of the signal (except those within one half of the window length from the extremities of the signal) spend equal amounts of time at the centre of the window.

Coyle et al. implemented a STFT approach to extract features from left and right hand movement EEG signals. The features were then classified by an LDA classifier. This study produced an average classification accuracy of 88.425% across 4 trials on 3 subjects [62]. Thus, a STFT approach to feature extraction may be a viable solution to online BCI.

### Discrete Cosine Transform (DCT)

The Discrete Cosine Transform (DCT) was developed by Chen and Pratt in 1984, and is similar to the DFT, however carries some advantages. Rather than decomposing the signal into a summation of sine and cosine functions (represented as complex exponentials), the DCT uses only cosines, and is thus completely real-valued. This reduces computational complexity [12]. The DCT coefficients, , for an -point signal, , can be computed by Equation (27) [63].

(27)

Additionally, through applying a zonal coding strategy, the coefficients obtained by applying Equation (27) can be compressed. A quantisation vector of values, , is devised such that:

(28)

Selective determination of the quantisation coefficients can reduce the amplitude of some frequency contributions to such a degree that they can be ignored, effectively compressing the signal [64]. The quantisation coefficients are often chosen such that the quantised signal described by possesses 90% of the power of the original signal described by . In many cases, this results in the high frequency DCT coefficients being eliminated, as the low frequency components of the signal possess more power [65]. Since EEG signals are usually low frequency, and any high frequency elements of the signal are generally noise or artefacts, this behaviour is desirable. Thus, the DCT process contains some inherent dimensionality reduction, which is favourable when performing online signal classification.

Applying the DCT to a time-frequency application introduces the modified discrete cosine transform (MDCT). This approach was developed by Princen and Bradley in 1986 to reduce the effect of time domain aliasing introduced by windowing the signal [66]. This approach consists of windowing the signal with 50% overlapped windows (i.e. the latter half of the first window includes the same data as the first half of the second window), then applying the DCT. When the inverse MDCT (IMDCT) is applied, each block introduces several artefacts. However, when the subsequent block of inverse transformed data is added, the errors introduced cancel out via time domain aliasing cancellation [67]. Since the recorded EEG signal will not need to be reconstructed in this application, the reconstruction errors introduced by time-domain aliasing artefacts will not be considered.

## Classification

There are several methods used to classify the features extracted from an EEG signal. Methods proposed by Wang et al. include Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM) prediction, and *k*-Nearest Neighbours (kNN) algorithms [14]. SVMs and LDA were observed to be widely used in classifiers [14, 58, 68, 69].

### Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) has historically been one of the most common classification techniques for BCIs. LDA aims to find a linear combination of features that can best separate two or more classes [13]. Following training of the classifier on a training data set, a set of eigenvectors representing each class is obtained. When a test observation is to be classified, the linear combination of features developed during testing is used to generate an eigenvector representative of the observation. The classifier then selects the class that produces the minimum Euclidean distance between the class eigenvector and the observation eigenvector [69]. As LDA is a machine learning approach, LDA classifiers can suffer from overfitting, especially when the training dataset is small. However, it is proposed by Pang et al. that regularising the data by unsupervised clustering can reduce the likelihood of overfitting [70]. Similarly, since this approach is linear, LDA tends not to suffer from overfitting as much as nonlinear classifiers [11] but must operate under the assumption that the covariance of each class is the same [71]. Wang et al. achieved a classification accuracy of 82.86% on the 2003 Gratz BCI Competition Dataset III when classifying motor imagery EEG signals. The authors concluded that LDA, as a linear classifier is suitable for BCI applications due to its simplicity and stability [14].

### Quadratic Discriminant Analysis (QDA)

Quadratic Discriminant Analysis (QDA) operates in a similar manner to LDA, however removes the assumption that the covariance matrices of each class is the same [72]. This removes the benefits discussed in Section 3.3.1 (resistance to overfitting) and introduces additional complexity. Wang et al. achieved a classification accuracy of 78.57% on the 2003 Gratz BCI Competition Dataset III when classifying motor imagery EEG signals [14]. Thus, QDA is not a competitive classification solution in this application.

### Support Vector Machines (SVM)

Support Vector Machines (SVM) are another popular approach to EEG classification. These systems again employ machine learning, however in this case the goal is to define an *n*-1 dimensional plane in *n*-dimensional Euclidean space that divides the data classes, where the Euclidean distance between each class is maximised [73, 74]. This is achieved by first finding the support vectors. These are *n*-dimensional vectors defining the data points that are closest to the hyperplane (that is, hardest to classify). There is a theoretically infinite number of hyperplanes that can divide the classes [75], thus the SVM solves a trivial optimisation problem to determine the optimal plane. Once a new data point is supplied for classification, the dot product of the new data point’s vector and the plane is taken to determine what side of the plane it falls on. This is very computationally simple. The elegance of SVMs surrounds their implementation of the “kernel trick”, which enables non-linearly separable data to be separated by defining additional separation functions called kernels. These kernels can include polynomials, exponentials, and sigmoids [76]. Wang et al. achieved a classification accuracy of 82.86% on the 2003 Gratz BCI Competition Dataset III when classifying motor imagery EEG signals using a Linear SVM, and 84.29% using a Gaussian SVM [14]. Thus, the SVM is a viable solution to the EEG classification problem.

### *k*-Nearest Neighbours (kNN)

A *k*-Nearest Neighbours (kNN) algorithm establishes each training data point in an *n*-dimension parameter space, which can be defined by a vector of features (the features are obtained by the methods outlined in Section 3.2). When a new data point is to be classified, it is placed into the same parameter space. The data point is then classified by a voting system, where the class of the new data is the class of the majority of its “*k*-nearest neighbours”, or *k* closest training data points [77]. There are several ways to calculate the “distance” between neighbouring data points. The most basic is Euclidean distance. However, measures such as cosine similarity, defined below, are also used in some applications (generally when the data to be classified is not sparse, creating large angular differences).

Where, is the similarity of data points and , and is the angle between data points and [78].

(29)

This calculation is not computationally intensive in lower dimensions. However, the kNN algorithm suffers drastically in higher dimensions, as almost the entire parameter space is required to find the closest *k* data points, particularly if the data points are not close to each other [79]. This increases computation time significantly. Thus, in order to be implemented in an online BCI system, an extensive (accurate) feature selection procedure is required.

Wang et al. achieved a classification accuracy of 84.29% on the 2003 Gratz BCI Competition Dataset III when classifying motor imagery EEG signals using a kNN approach [14]. Thus, the kNN approach is a viable solution to the EEG classification problem, however would require additional feature selection to be viable in an online classification setting.

## Simulation

As noted previously, most publications collate classification results comparing feature extraction or classification techniques using different datasets. By applying the approaches established above to a single dataset, relative performance can be assessed, and the optimal system can be determined, from which a system can be designed and implemented.

### Simulation Methodology

Using the dataset published by Kaya, et al. [80], classifications made by Quadratic, Gaussian, Radial Basis Function (RBF), Polynomial and Linear SVMs, LDA, and kNN classifiers were compared when supplied with features extracted by STFT and DCT methods. The classification time and accuracy of each approach was compared, and the optimal system was defined as the system that produced the highest classification accuracy per unit time.

The dataset contains EEG recordings from a healthy 20-25 year-old female with no prior BCI experience. There are recordings from 19 10-20 system recording sites, referenced to two ground leads attached to the earbuds. The signals were 0.53 – 70 Hz bandpass filtered by the recording software, and recorded at 200 samples per second. The amplitude resolution of the recordings was 0.01μV at 24 bits. The data was recorded in a synchronous BCI paradigm (i.e. the start and end times of the event were dictated by software, not the user). When an event was started, a stimulus was provided on a screen for 1 second, during which the subject imagined the corresponding movement (right hand closed, left hand closed, or idle). Following the 1s stimulus, a random screen-off time of 1.5 – 2 seconds occurred, allowing the subject to reset between events. The stimulus was encoded into the dataset [81].

To evaluate each extraction and classification technique, first the EEG data was low-pass filtered using a 10th order Butterworth filter with a cut-off frequency of 30 Hz. The data was then epoched. This was achieved by identifying the rising edge of the “marker” signal (i.e. where the stimulus changed from “idle” to “right hand”, “left hand”, or “rest”), then saving the following 2 seconds of data in its own vector. To enable 2 class classification, “left hand” trials were removed. The C3 data was then multiplied by a Hanning window to reduce the frequency domain artefacts, and the data from other channels was disregarded.

In the STFT case, by applying a 215-point FFT to the 2 second epoch, the frequency spectrum of each event was calculated. By observing the time-frequency distribution across all trials, it was clear that all the activity was bounded below the 2458th frequency bin, so these low-frequency bins were selected as features. This distinction can be seen by observing Figure 7.



(a)

(b)

Figure 7 - Heatmaps of spectral power obtained by taking the STFT of the EEG dataset presented in [81]. (a) shows the full feature vector, while (b) limits the features to below 2458 Hz.

In the DCT case, the DCT coefficients of each 2 second epoch were determined, and these coefficients were used as the classification features. No further feature selection was required, as the DCT exhibits inherent dimensionality reduction.

The sets of features were passed to several classifiers. The classifiers were as follows:

1. Linear SVM,
2. Gaussian SVM,
3. RBF SVM,
4. Polynomial SVM,
5. LDA, and
6. kNN (15 neighbours).

Each classifier had a holdout percentage of 20%. The time taken to classify the remaining datasets was measured using MATLAB’s tic and toc functions. Training time was not included, as in the proposed system, the model will be trained offline, then applied online. The simulations were run using MATLAB 2016a on a system consisting of an Intel Core i7-5500U (2.4 GHz) with 16 GB of DDR3 RAM (1600 MHz).

### Simulation Results

Figure 8 shows the accuracy of each of the classification algorithms when classifying the STFT feature set. Under this approach, the Linear SVM had the greatest accuracy, 71.70%. This was achieved in 0.0148 seconds. This gave the Linear SVM the highest overall score of 48.52. The accuracy, classification time, and score of each classifier is presented in Table 1.

Figure 8 - A graph showing classification accuracy for several classifiers when supplied with the STFT feature set.

Table 1 - A summary of classification results obtained using the STFT feature set.

|  |  |  |  |
| --- | --- | --- | --- |
| Classifier | Accuracy (%) | Classification time (seconds) | Score |
| Linear SVM | 71.70 | 0.0148 | 48.52 |
| Gaussian SVM | 50.94 | 0.0534 | 9.54 |
| RBF SVM | 50.94 | 0.0526 | 9.69 |
| Polynomial SVM | 66.04 | 0.0266 | 24.86 |
| LDA | 50.31 | 0.0311 | 16.16 |
| kNN | 64.78 | 0.0774 | 8.37 |

Figure 9 shows the accuracy of each of the classification algorithms when classifying the DCT feature set. Again, the Linear SVM had the greatest accuracy, 74.59%. This was achieved in 0.0038 seconds. This gave the Linear SVM the highest overall score of 196.30. The accuracy, classification time, and score of each classifier is presented in Table 2.



Figure 9 - A graph showing classification accuracy for several classifiers when supplied with the DCT feature set.

Table 2 - A summary of classification results obtained using the DCT feature set.

|  |  |  |  |
| --- | --- | --- | --- |
| Classifier | Accuracy (%) | Classification time (seconds) | Score |
| Linear SVM | 74.59 | 0.0038 | 196.30 |
| Gaussian SVM | 50.79 | 0.0095 | 53.46 |
| RBF SVM | 50.79 | 0.0075 | 67.72 |
| Polynomial SVM | 50.79 | 0.0038 | 133.66 |
| LDA | 67.02 | 0.0079 | 84.84 |
| kNN | 48.69 | 0.0210 | 23.185 |

These results clearly show the improvements in classification time brought about by the DCT’s reduced feature set. Classification accuracies remained similar between the two approaches. Therefore, due to the significant decrease in classification time, the optimal feature extraction technique analysed is the DCT. While the DCT has been extensively studied in the field of image compression [65, 82, 83], applying the DCT to EEG classification is a novel approach, which may carry several benefits, including reduced classification-space dimensionality, leading to reduced classification time. This is especially attractive to online BCI systems, where classification time is necessarily as short as possible.

# Proposed System

Following the completion of the simulation, the most advantageous system had been identified. This enabled a proposed system to be developed. Figure 5 now can be considered as shown in Figure 10.

Figure 10 - A modified system block diagram, indicating the selected functional blocks of the proposed system.

The architecture of such a system could be designed as presented in Figure 11.

Figure 11 - A schematic diagram showing the implementation blocks and interfaces for the proposed system.

## EEG Hardware

Following the literature review, it was clear that dry electrodes would be preferential to wet electrodes due to their single person operation and reduced setup time. After comparing suppliers, Florida Research Instruments (FRI) offered an extensive range at a reasonable cost. They offer package deals, bundling an EEG headband with several dry electrodes and leads. The headband does not offer the full 10-20 location set, however it includes several key sites, including C3 and C4. The headband is shown in Figure 12.

Figure 12 - A photo of the Florida Research Instruments EEG Headband [84].

The proposed system will only require 1 EEG channel (C3), however several electrodes will be purchased for potential future expansion by the University of Newcastle. Additional to the signal electrode, the system requires a ground electrode in the form of an ear clip. FRI offers these devices. The final bill of materials for the EEG hardware is presented in Table 3.

Table 3 - Bill of Materials for EEG Hardware.

|  |  |  |  |
| --- | --- | --- | --- |
| Item | Quantity | Price (AUD) | Notes |
| Basic EEG Headband Package | 1 | $104 | Includes:   * 15 Dry Electrodes * 10 Wet Electrodes * An EEG Headband * 5 Leads |
| Silver/Silver-Chloride Ear Clip | 1 | $29.62 |  |

## Data Acquisition System Hardware

The signal detected by the electrodes will be processed by the data acquisition system. This system contains passive filtering components, analog to digital conversion, and wireless transfer, facilitated by an ATmega328P microcontroller. The design criteria for this system include a small footprint, since it will be mounted to the head of the subject, and power efficiency, to enable battery operation (reducing the impact of rectification or switched mode power supply noise on the analog signals).

The incoming EEG signals will be passively low-pass filtered, using an RC filter with a cutoff frequency of approximately 30 Hz. While this filter is of lower order than that used in the simulation, it will still offer adequate rejection of high-frequency noise. The filtered signal will then be digitised using a delta-sigma ADC. The Texas Instruments ADS1299 was found during the literature review to be a high-performance ADC with several EEG-specific features [47-52]. To facilitate future expansions, the Data Acquisition System will be designed to allow the operation of all 8 channels available on the ADS1299 model. This was completed despite this application only requiring 1 channel, which could have been adequately served by the lower-cost, 4-channel ADS1299-4. The ADS1299 will sample the input signal (referenced to the reference electrode) at 250 samples per second in continuous conversion mode. This sampling frequency is sufficiently high to detect the low-frequency signals present in EEG, and is higher than the sampling frequency used in the data published in [81].

The data will be read from the ADC over an SPI bus by the ATmega328P. The microprocessor will then perform a simple conversion to UART data, which will be sent by an HC-05 UART to Bluetooth module to the mainboard for feature extraction and classification. The layout of the Data Acquisition System is presented in Figure 13, and a render of the board is presented in Figure 14. The schematics of the Data Acquisition System are presented in Appendix A – Data Acquisition Board Schematic.

Figure 13 - The PCB layout of the Data Acquisition Board.

Figure 14 - A 3D render of the Data Acquisition Board.

Power can be supplied to the board through a DC connector, capable of regulating 16 V. The linear regulator used has a dropout voltage of less than 1V at full load, so the device can alternatively be powered by connecting 4 AA batteries in series to the battery connection header. This will increase portability and reduce conducted EMI from a mains-powered rectifier and switch mode power supply. The completed layout has a board area of 95mm × 60mm, which is small enough to comfortably attach to posterior portion of the EEG head strap.

The interface specifications for this board are presented in Table 4.

Table 4 - Interface specifications for the Data Acquisition board.

|  |  |  |
| --- | --- | --- |
| Interface | Connector | Notes |
| Analog Signal Input | J1 | 8 Data Signals (Pins 1 – 8), 1 Reference Signal (Pin 9) |
| Serial-over-USB | J2 | Mini-USB port to UART facilitated by FTDI chip. FTDI drivers required. SW2 must be set to enable USB communication. |
| Battery Power In | J3 | 6V – 16V battery connection from daughter board. SW1 must be enabled to connect battery. |
| DC Power In | J4 | 6V – 16V DC barrel jack. |
| Bluetooth | J5 | UART to Bluetooth module header, suitable for HC-05. SW2 must be set to enable Bluetooth communication. |
| ICSP | J6 |  |

## Data Acquisition System Software

The software for the ATmega328P on the Data Acquisition board will establish a connection with the ADS1299, set up the ADS1299 for the required configuration, establish a connection with the Bluetooth module, and facilitate real-time data transfer between these two devices.

### SPI Timing Requirements for ADS1299

There are several timing requirements for the SPI interface of the ADS1299. When the device is first addressed by taking the LOW, there must be a 6 ns delay between LOW and the rising edge of SCLK. The SCLK frequency is determined by Equation (30), from the ADS1299 datasheet [54].

(30)

where is the period of the serial clock, , is the period of the master clock, is the ADC resolution, and is the number of channels being sent. In this application, , since the requested data rate is 250 samples per second. , and is defined by the internal oscillator of the ADS1299. , since each reading is a 24-bit value, and , since the project is using the ADS1299 chip (8 channels) rather than the ADS1299-6 (6 channels) or the ADS1299-4 (4 channels). Substituting these values into Equation (30) yields a , equivalent to an .

When sending multi-byte commands, a period of must elapse between each byte. is defined as 4 clock periods. The internal oscillator is being used in this application, which has a period of 2.048 MHz. Therefore, .

### Configuring and Operating ADS1299

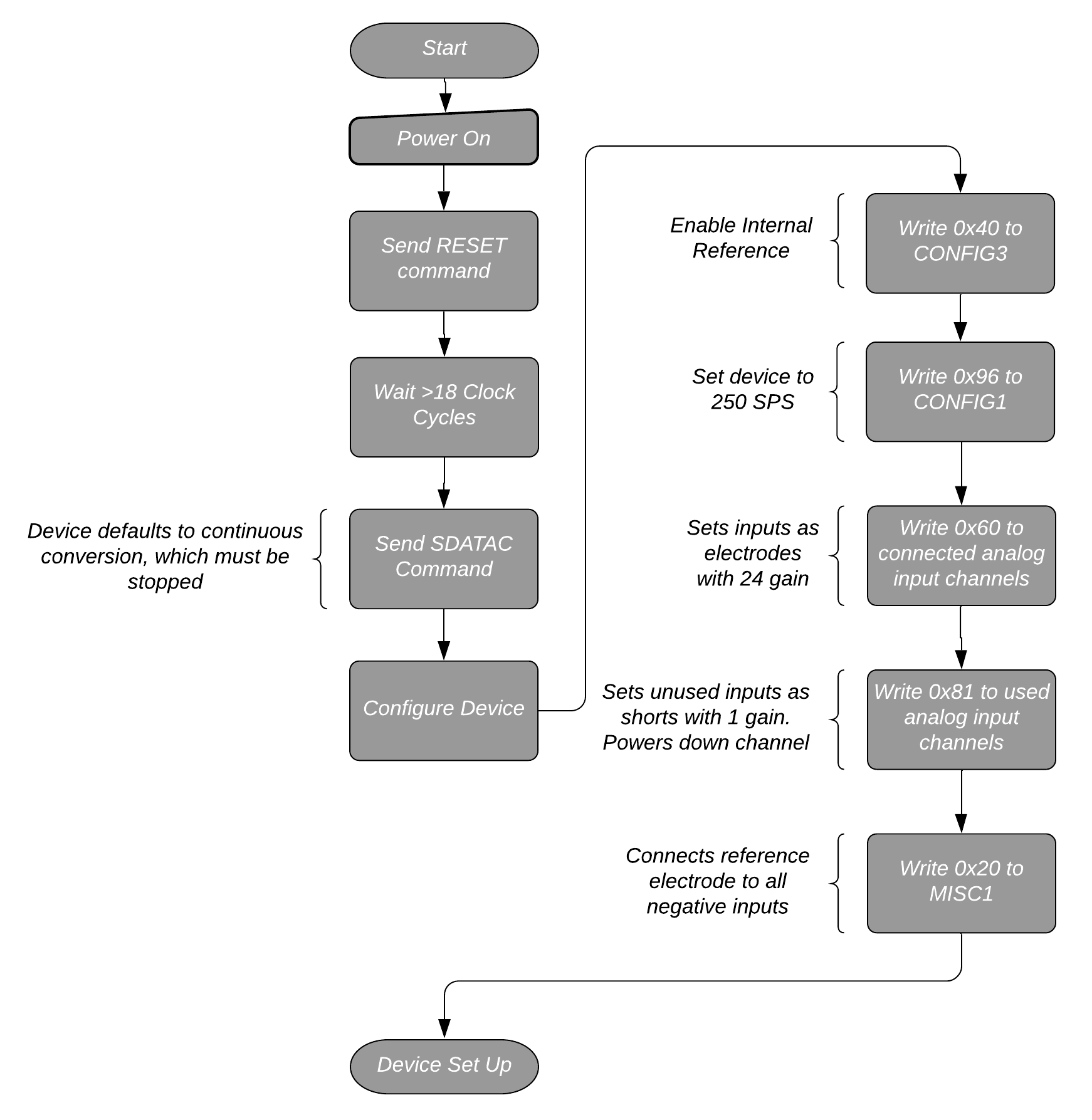
The ADS1299 is an extremely versatile biosignal analog front end. To configure its many parameters, it has several configuration registers that must be set appropriately for each application. These registers are configured by writing commands over the SPI interface. The SPI interface is set to operate in SPI Mode 1 (CPOL = 0, CPHA = 1).

Figure 15 indicates the process of configuring the ADS1299. Once the flow chart in Figure 15 has been completed, the device is ready to start the data conversion. This is triggered by setting the START pin HIGH, or setting the START pin LOW and sending the START command over the SPI bus. Once the conversion has started, the DRDY pin should be monitored. When the DRDY pin goes LOW, there is 1 sample of data in the output shift register. The RDATA command can be used to retrieve the data. During this read action, no data should be written to the MOSI line. The data will arrive in 9 24-bit packets, MSB first. The first packet is a STATUS packet, containing lead-off and GPIO information. The remaining 8 packets contain the channel data, starting with Channel 1 and ending with Channel 8. This data can be processed, and sent over the serial bus as required, then the DRDY line should be monitored again, waiting for more data.

The ADS1299 has 10 functions, which will be enumerated, allowing for wrapper functions to be called using a switch-case structure. This will provide a higher-level interaction layer than what would be used if the protocol was interacted with directly.

### Processing and Transmission

The data from the ADS1299 will then simply be sent over the UART serial bus to the Bluetooth module, where it will be transmitted to the Classification and Control board. An overview of the whole software system is presented in Figure 16.

Figure 15 - ADS1299 configuration flowchart.

## Classification and Control Hardware

Once the EEG signal has been acquired and communicated over Bluetooth, the signal must be classified using a linear SVM to determine the motor intent of the operator. First, the discrete cosine transform will be applied to the signal, extracting the classification features. These features will be in the format of a vector. This vector is passed to the linear SVM classifier, which will determine if the subject is imagining a “hand open” or “hand closed” event.

Training of the linear SVM model will be conducted offline. Once the EEG hardware has been acquired, it will be determined if the dataset provided by Kaya et. al in [81] is representative of the data acquired in this application. If this is true, the data in [81] will be used as training data. However, if the differences are too large, and a reliable classifier cannot be trained using this data, a training paradigm will be devised to train the SVM using data acquired using the system outlined in this report. This training paradigm will be discussed further in Section 5.2.

Figure 16 - Software module interface diagram for the Data Acquisition board.

It is anticipated that the feature extraction and classification will be implemented on an STM32F407VET6TR Cortex-M4 based microcontroller from ST Electronics. This processor was selected due to familiarity with the system and experience with the discovery board. Additionally, it operates with a 32-bit architecture, enabling greater precision and speed during arithmetic operations [85]. Similarly, the 168MHz clock speed will be sufficient to apply the DCT and classify the signal online. There is significant documentation to accompany this chip, which may serve to reduce design complexity.

The PCB for the classification and control board will be developed next semester. Until that time, exact interface specifications remain to be determined. Subsequently, Table 5 is subject to change.

Table 5 - Interface specifications for the Classification and Control board.

|  |  |  |
| --- | --- | --- |
| Interface | Connector | Notes |
| Bluetooth | TBD | UART to Bluetooth module header, suitable for HC-05. This will communicate with the Data Acquisition Board or Android App. |
| SWD | TBD | A single wire debugging programming header, for use with an ST-LINK V2 programmer. |
| DC Power In | TBD | 6V – 16V DC barrel jack. |
| Servo Headers | TBD | 6 × 3 pin headers to power and control the servos. One connector per finger, one for the wrist. |

The control and classification board will be installed inside the prosthetic arm. Using Autodesk Tinkercad, the boundaries of the arm void were determined. These are presented in Figure 17.

Once the classifier has determined the state of the hand, an appropriate PWM control signal will be distributed to each finger, which will be present at each of the servo connection headers.

It is predicted that the Classification and Control Software will follow and architecture similar to that presented in Figure 18.

## 3D Printed Prosthetic Arm

The end effector of the system will be a 3D printed prosthetic arm. This device will serve as visual feedback for the subject. The arm was designed by Gael Langevin, and has gained popularity as a section of the InMoov 3D printed humanoid robot. These designs are freely available, and were selected for their detailed assembly instructions, low cost, aesthetics, and global community of makers, who were of great assistance during the assembly process. The arm consists of approximately 26 .stl files, which were printed by Phillip Dombkins at the University of Newcastle.

The arm was printed on a Markforged 3D printer using Onyx carbon fibre filament. This printer was capable of printing to an extremely high resolution, contributing to the ease of assembly. Additionally, the printed structures are lightweight and exhibit excellent structural rigidity, both characteristics favourable to prosthesis design [86].

The main components of the arm are the servo bed (which houses the 5 servos for the fingers and is located in the forearm), the wrist, and the hand. The servo bed was designed to accommodate 5 standard size servos. The Tower Pro MG946R servo is recommended, and has been used in this project. Due to the space constraints within this wrist cavity, a smaller sized servo, the Tower Pro MG996 was used. These servos

Figure 17 - A CAD model of the prosthetic forearm, with a shape representing the maximum PCB area.



Prosthetic Forearm

Maximum PCB Area

52.00mm

62.85mm

have a rated stall torque of 13 kg/cm, and draw 1.2A at locked rotor. Due to the high current rating of these servos, supplying adequate current to operate 5 servos simultaneously is a rigid design criterion which must be considered when the classification and control board is designed. The hand operates by rotating the servos inside the forearm. Ligaments of nylon braid connect each side of the servo horn to the fingertip of the corresponding finger. When closing the hand, the servo horn turns through 180o, increasing the tension on the tensor ligament running along the superior side of the hand, while simultaneously decreasing tension on the extensor ligament on the inferior side of the hand. This causes the finger to contract. The fingers are hinged by slotting a pin of filament into the holes located at the joints. The pins are then

Figure 18 - Software module interface diagram for the Classification and Control board.



friction mounted to the external casing of the hinge, while the internal component is free to rotate.

The arm was straightforward to assemble. Minimal tools were required, as most of the components were secured using Phillips head screws or Loctite 401. Loctite 401 was used on recommendation from Loctite for fusing nylon components. Other cyanoacrylates may produce a less successful bond between the components. Photos of the arm during assembly and post-assembly are presented in Figure 19.

## Demonstration Hardware and Software

To facilitate demonstration of the arm during the interim seminar, a demonstration board possessing minimal functionality has been developed and fabricated. This board can activate the 6 actuation points in the prosthetic arm, and is controlled via Bluetooth using an Android app.

### Demonstration App

The demonstration app was developed rapidly in MIT App Inventor 2, a web-based Android app programming tool. The app prompts users to connect to the arm by presenting them with a list of paired Bluetooth devices. Once connected, the 6 sliders (1 for each servo) become active. When the position of a slider is changed by the user, the app sends “<Servo\_Name>: <position>\n” where <Servo\_Name> is the servo being controlled, e.g. “wrist”, and <position> is the slider position in percent, where 0 corresponds to fully closed and 100 corresponds to fully open. Additionally, there are 3 buttons along the bottom of the screen to set the hand to preselected



(a)



(b)



(c)

Figure 19 - (a) The inferior surface of the constructed arm. (b) the superior surface of the constructed arm. (c) the arm being assembled, with the cover removed.

poses: fist (all fingers at 0), point (all fingers at 0 except the index finger, which is at 100), and open (all fingers at 100). The commands are terminated using a newline character. This app represents basic functionality, and is the minimum viable system to demonstrate the function of the prosthetic hand.

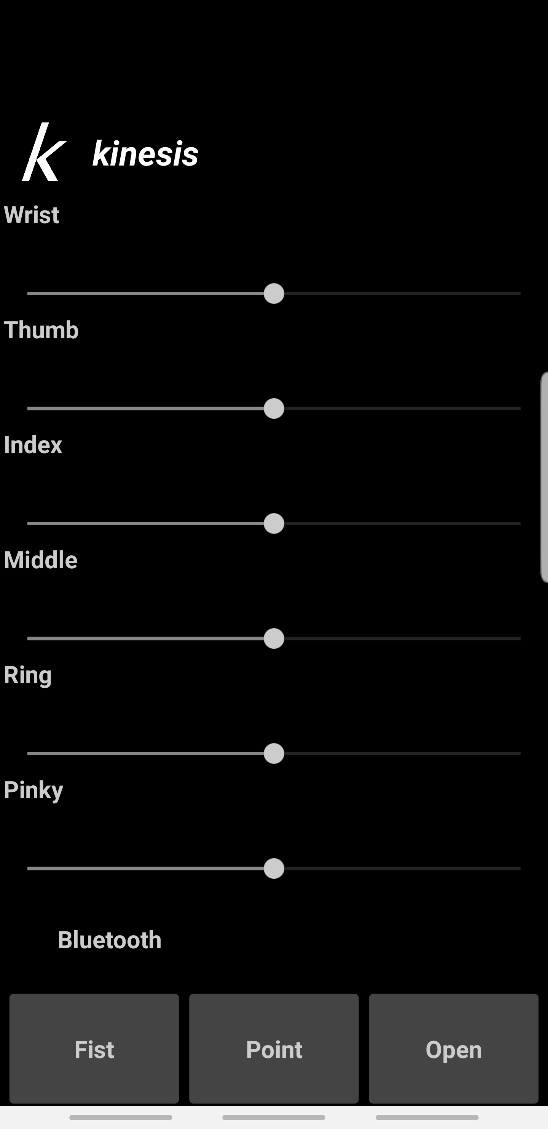
A screenshot of the app is presented in Figure 20.

Figure 20 - A screenshot of the demonstration app.

### Demonstration Board Hardware

A smaller cavity was found in the arm, and it was proposed that the demonstration board fit in this cavity. The dimensions of the cavity are approximately 70 × 30mm. The limited available space restricts the demonstration board to including the minimal hardware required to operate the arm wirelessly. This limits the components to:

1. an Arduino Nano, soldered directly to the PCB,
2. an HC-05 Bluetooth Module, soldered directly to the PCB,
3. a DC power jack, and
4. the 6 servo headers for the servos.

Building the demonstration board around the Arduino Nano accelerated the development of this board. The Arduino Nano is self-contained, so it was not necessary to devote time to designing the power circuits, oscillators, indicator LEDs, etc. Similarly, the UART to USB interface was also included. This limited the hardware design to simply arranging the peripheral hardware. The layout and render of the demonstration board is presented in Figure 21. One drawback to this design is that the Arduino cannot be reprogrammed once it has been soldered to the device, as the serial programming ports are shared with the Bluetooth module, which cannot be disconnected. A second iteration of this design would have included a switch to disconnect the Bluetooth Module. Headers could not be used due to the limited vertical space.



(a)

(b)

Figure 21 - (a) the PCB layout of the demonstration board, and (b) a 3D render of the demonstration board.

### Demonstration Board Software

The software required to operate the demonstration board is minimal. The basic flowchart is presented in Figure 22.

The program will continue to read from the buffer until there is a newline character. Once this has occurred, the string will be parsed to distinguish between the desired actuator and the position. The actuator string will be compared against the items of the list of known actuators. If a match is found, the duty cycle of the signal being passed to that actuator will be set to the required value. If no match is found, the command is ignored. This is the minimal software required to demonstrate basic functionality.



Figure 22 - A flowchart of the demonstration software.

# Progression Tasks

There are various phases required to test the functionality of the system. Initially, tests will focus on validating basic hardware functionality. These tests will be gradually built on until full system capability tests are conducted. Testing progress will be recorded in a Test Register to monitor system performance. Additionally, due to differences between the real-world signals and data published in [81], it may be necessary to define a training paradigm to generate data used to train the SVM model.

## Testing and Evaluation Processes

### Functionality Testing of ADS1299

To test the functionality of the ADS1299, a 1Vpp sine wave will be applied with a DC offset of 1.5V. This signal remains between 0.3V of the voltage supply rails, and therefore within the linear range of the ADC [54]. The serial data will be read using the serial plotter feature of the Arduino IDE. This will test if the ADS1299 has been set up correctly, and can examine the effect of the programmable gain feature of the device.

### EEG Data Acquisition using the ADS1299

Once the working condition of the ADS1299 has been established, real-world EEG data can be recorded. This will establish the working condition of the EEG electrodes, and identify any impedance or scalp contact issues that may occur. It will also be a full-system test of the Data Acquisition Board. The EEG signal should be present on the serial plotter of the Arduino IDE.

### Establishment of the Bluetooth Link

The next test will establish a Bluetooth connection between the data acquisition board and the classification and control board. Sending and receiving a “Hello World” message will be sufficient evidence to pass this test. This test will ensure the serial communication between the ATmega328P and its Bluetooth module, and the STM32F407VET6TR and its Bluetooth module, is set up correctly.

### Generation of the PWM Control Signal

It is critical that the classification and control board can generate the 6 required PWM signals simultaneously. This test will be passed if 6 unique PWM signals can be observed on the oscilloscope. These signals can then be used to control the prosthetic hand.

### Calculating the DCT

The classification and control board needs to calculate the DCT of a signal in real time. This includes multiplying the signal by a Hanning window function. The signal will be simulated using a section of EEG data from [81]. Using a DCT library, the DCT of the signal will be calculated. The output vector will be compared to the output vector calculated using MATLAB. Any variance will be noted, and appropriately adjusted. Success will be classified as conformance with the MATLAB result.

### Testing the SVM

Using a model trained on a PC, the SVM on the classification and control board will be evaluated for classification accuracy and time. Performance compared to the PC-based SVM will be recorded. Success will be achieved if the accuracy of the on-board SVM is similar to the PC-based SVM. It is anticipated that the classification time of the on-board SVM will be higher than the PC-based SVM. If it is not feasible to classify the data online using the slower SVM, additional feature extraction will be considered to reduce the dimensionality of the observation vectors.

### Classifying Real Time Data

Once the Control and Classification board has been successfully evaluated, it can be paired with the tested and working Data Acquisition board to classify real-time data. This test can be conducted by writing a digital HIGH to a pin representing one class, or a digital HIGH to a different pin representing the other class. Success rate can be calculated using software. If the classification accuracy is sufficiently high, the test has been completed.

### All Together Now!

Once all the constituent parts have been tested and evaluated, and all the interfaces have been shown to operate successfully in real time, the whole system can be integrated. This will result in the acquisition and real-time classification of EEG brain waves, resulting in a 3D printed prosthetic hand executing the motions imagined by the subject.

## Generating Classifier Training Data

Due to differences in data acquisition systems and recording conditions, and biological differences between subjects, the data published in [81] may not be a suitable dataset to use for training the SVM classifier. If this is the case, training data must be generated using the system proposed in this project.

### Training Data Acquisition Setup

Since training is a memory-intensive process [87], it is proposed that the training of the model be conducted using MATLAB, on a PC. This mandates an interface between the Data Acquisition Board and a PC. This has been achieved through the inclusion of an FTDI chip, which (with the appropriate drivers) will open a COM port on the PC. When the Data Acquisition board is connected to the PC using a Mini-USB cable, MATLAB can connect to the COM port and read the EEG data in real time.

### Training Paradigm

SVMs are supervised classifiers [88]. Therefore, when using test data to generate a classifier, the computer must know which class the data belongs to. This will be achieved by issuing a prompt to the user, which will then be stored with the corresponding EEG data (similar to the “Marker” channel in the data published in [81]). The training paradigm is proposed to follow the timeline presented below.

Table 6 - Proposed classifier training data acquisition paradigm.

|  |  |
| --- | --- |
| Time (s) | Event |
| 0 - 1 | Blank Screen (Fixation Cross) |
| 1 - 2 | Cue Given (Green or Red Dot) |
| 2 - 4 | Blank Screen |

This training paradigm is similar to that presented in [81]. The first second consists of a “rest” period, where the subject will fixate on a cross at the centre of the screen. The fixation cross serves to reduce oculomotor artefacts, which may otherwise couple into the EEG signal [89]. Similarly, by using a simple colour cue to encode “hand open” or “hand closed,” rather than a lexical cue, will reduce eye movement. The cue will remain on the screen for 1 second. Following this, the screen will go blank for a further 2 seconds.

The EEG data recorded from the COM port will be saved as a vector (vector length will be 4 seconds × 250 samples per second = 1000 samples long). This vector will form a component of a data structure, along with a string indicating “hand closed” or “hand open” and an integer encoding the same information, 1 representing hand closed and 0 representing hand open.

The recorded and processed data will then be used to train a linear SVM model. The number of test datapoints required is not known at this time, however the simulated classifiers in Section 3.4 used 611 datapoints, with a holdout percentage of 20%. This number may vary with the quality of EEG data. Poorer quality data will contain more artefacts and EMI, reducing the class separation and thus reducing classification effectiveness.

# Conclusion

At the completion of this semester, an extensive understanding of the current state of BCI research has been attained. Through this understanding, knowledge of the advantages and disadvantages of each approach has been gained. This knowledge, supplemented through a simulated comparative analysis, led to the development of the optimal system architecture. This system will use dry electrodes to measure neural activity during imagined grasping, then extract classification features using the DCT. The application of the DCT to EEG analysis is a novel approach. The feature vector will then be classified using a linear SVM, the output of which will be used to control a 3D printed prosthetic hand. The implementation of the system requires the design and construction of a wireless EEG data acquisition system, and a classification and control system, which is to be installed in the prosthetic hand. A clear path forward has been devised, to increase the probability of project success at the completion of next semester.

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# Appendix A – Data Acquisition Board Schematic



